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The Impact on Consumer Behavior of Energy Demand Side Management Programs Measurement Techniques and Methods

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by

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Much effort has gone into measuring the impact of Demand Side Management (DSM) programs on energy usage, particularly in regards to electric usage. However, there are potential biases in such measurements. This paper explores one of these potential biases, the rebound effect. This effect is caused by changes in consumer behavior as a result of DSM programs. The work of Steven Braithwaite and Douglas Caves provide the starting point for this analysis, although the rebound effect is referenced in many other works in this field.

In an effort the estimate this effect, data from the Nebraska Energy Office's DSM programs was utilized. Econometric and survey techniques were employed to isolate changes in energy usage solely related to the DSM programs. Further econometric techniques were used to separate the resulting behavioral change from the change resulting from the DSM investment itself. Additionally, the returns to scale regarding DSM investments were estimated.

Based on the available data, a distinct behavioral change was observed. The observed behavioral change was more pronounced among lower income households. Many of the DSM investments exhibited diminishing returns to scale.

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Chapter I – Introduction

1. Demand Side Management in Nebraska

Demand side management ("DSM") is a term which refers to efforts that seek to reduce energy demand by encouraging consumers to adopt energy efficiency measures. DSM programs emerged in the 1970s in response to rising oil and gas prices and perceived long-term shortage in energy supply[1]. Initially, DSM programs were developed and employed by energy providers. However with the advent of energy deregulation, the responsibility for the implementation and on-going management of DSM programs has in many instances shifted to agencies and departments within state government[2]. In Nebraska, a collection of DSM programs are administered by the Nebraska Energy Office (NEO).

Over the years, DSM programs have employed different tools to encourage and facilitate energy savings through inducing behavioral changes and the deployment of more efficient energy appliances and equipment. These tools include[3]:

- Time of Use pricing
- Smart Meters
- Informational Campaigns
- Technology replacement
- Voluntary and Compulsory Energy Rationing
- Energy Load Shedding and Control

In some instances, DSM is employed to reduce peak demand requirements. Energy production and distribution networks are typically built to accommodate peak

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[1] David S. Loughran and Jonathan Kulick, *Demand-Side Management and Energy Efficiency in the United States*, (The Energy Journal, Vol. 25, No. 1, 2004), 19.
[2] Loughran and Kulick, *Demand-Side Management*, 21.
[3] Sara Bryan Pasquier, *Saving Electricity in a Hurry: Update 2011*, (International Energy Agency, June 2011), 19.

energy load requirements. Reducing energy usage in the peak times can generally lower energy provisioning costs. Strategies employed to reduce peak load demand include time of use pricing and the load shedding which are engineered power outages commonly referred to as rolling blackouts.

Another tool employed in DSM programs is the creation of incentives for consumers to deploy technologies which require less energy usage. Such incentives often encourage the replacement of appliances such air conditioners and furnaces with more efficient units, the addition of heat pumps, and investments in other energy efficient technologies. The replacement of traditional light bulbs with compact fluorescent lamp ("CFL") and light emitting diode ("LED") technologies is another method often employed to reduce energy consumption. These replacements are achieved through the deployment of various financial incentives, such as reduced costs, low interest or shared loans, or for low income consumers, the direct replacement of older appliances and supporting infrastructure with more efficient substitutes. The impacts that such incentive programs have on consumer behavior are the focus of this paper.

This study focuses on the "Low-Income Replacement and Retrofitting Program", commonly referred to as the Low Income Weatherization Assistance (Weatherization) Program, and the "Nebraska Dollar and Energy Savings Loan Program", commonly referred to as the Energy Loan (Loan) program which were developed and have been operated by the Nebraska Energy Office (NEO). The NEO has operated the federally funded Low Income Weatherization Assistance Program since 1979. Collectively, the low income weatherization and energy loan programs are referred to as the NEO's DSM programs.

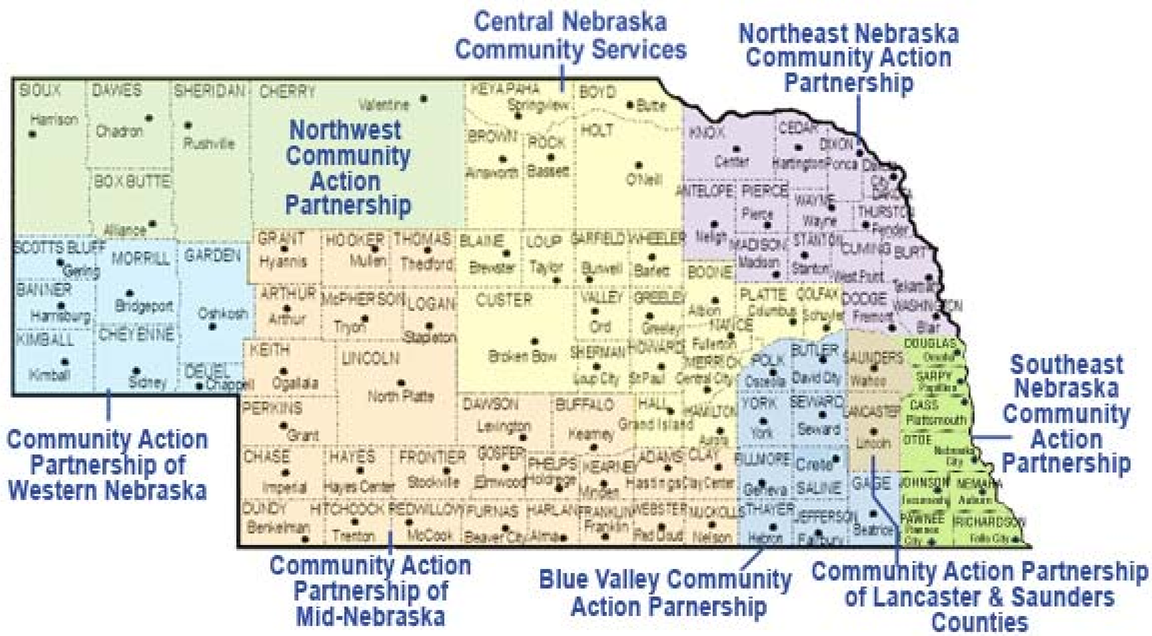
The NEO's Weatherization Program provides qualifying low-income consumers with replacements for less efficient appliances, improved insulation, and generally improves the overall weatherization of the consumer's dwelling. Services are provided by nine non-profit organizations, each of which typically operates in a unique part of the State. The non-profit organizations provide weatherization program services through a combination of in-house personnel, outside contractors, and local retailers. This study encompassed five of these providers:

- Central Nebraska Community Services (CNCS);
- Southeast Nebraska Community Action Partnership (SENCA);
- Northwest Community Action Partnership;
- Community Action Partnership of Western Nebraska; and
- Community Action Partnership of Mid-Nebraska.

Below is a map of the areas served by each provider[4].

[4] During the study period, Weatherization Trust provided services in Douglas County. Subsequently, Southeast Nebraska Community Action Partnership has taken over the provision of weatherization services in Douglas County.

Figure I.1
Map of Weatherization Provider Service Areas



The five providers included in this study collectively provide weatherization services to 40% of the households, 39% of the population, and 80% of the land area in Nebraska.

2. DSM Literature Review

In 1994, Steven Braithwait and Douglas Caves (BC) argued that traditional measures of the cost-effectiveness of utility-funded DSM energy efficiency programs suffer from three conceptual biases[5]. These biases are described in more detail below.

[5] Steven Braithwaite and Douglas Caves, *Three Biases in Cost-Efficiency Tests of Utility Energy Efficiency Programs*, (The Energy Journal, Vol. 15, No. 1, 1994), 97-98.

1. **Rebound Effect.** Failure to account for changes in consumer behavior. DSM programs typically make it less costly for consumers to improve their energy efficiency. Qualifying consumers can purchase more energy efficient technologies at lower costs. In many cases, the consumer bears no cost associated with energy efficiency investment. Absent behavioral changes by the consumer, the improvement in energy efficiency will reduce the amount of energy purchased by a consumer. Consumers may use the savings to improve their respective welfare, and in some cases, this may take the form of increasing the amount of energy used. An example is that a consumer who installs a more efficient furnace may opt to keep the temperature at 70 degrees in the winter rather than 68 degrees.

2. **Energy Prices.** Failure to fully account for changes in electricity prices. DSM programs are designed to reduce energy usage. Energy providers set prices to recover costs associated with energy generation and distribution based upon a given level of energy usage. The reduction in energy usage, if significant, may result in realized revenues from consumers being below the required level for cost recovery. Thus energy providers may need to raise prices in response to the reduced energy consumption caused by DSM programs.

3. **Free Riders.** Failure to account for different degrees of imperfections in the energy efficiency markets. If, as most studies of DSM programs indicate, the long run benefits of investments in more energy efficient technologies exceed the costs, it would be expected that many consumers would make the investments

without the need for the financial incentives of a DSM program. Thus benefits accrued to DSM programs may well have been realized without the cost associated with such programs.

Regarding the first bias, the rebound effect, BC defined the observed change in energy usage, prior to price responses, as

$E^0 - E^1 = (F^1 - F^0) * (1 - b)\ with$

- $E^0 = \ Energy\ Usage\ before\ DSM\ Measures$
- $E^1 = \ Energy\ Usage\ after\ DSM\ Measures$
- $F^1 = \ Energy\ Efficency\ Measures\ (EEMs)\ after\ DSM\ Measures$
- $F^0 = \ Energy\ Efficiency\ Measures\ (EEMs) before\ DSM\ Measures$
- $b = \ Behavioral\ Response, the\ "rebound\ effect"$

BC took a macro approach and defined the entire market for energy efficiency measures using EEMs. EEMs are associated with devices or features on energy using appliances and systems that increase the technical efficiency by which energy is converted for its intended purpose[6]. EEMs are measurements in units of energy equivalents such as kilowatt hours (kWh) or therms, for electrical usage and natural gas usage respectively. In essence, EEMs represent the expected energy savings associated the installation of a given appliance or system. In the above formula, the term F^0 represents EEMs purchased in a given market, excluding those which were purchased as a result of DSM measures. The term F^1 represents total EEMs purchased in the same market and includes those purchased as the result of DSM measures. Thus, $F^1 - F^0$ is equal to the amount of EEMs which are purchased as the result of DSM measures.

[6] Braithwaite and Caves, *Three Biases*, 99.

As policy makers consider the benefits of DSM programs, measuring the cost effectiveness of DSM programs has become increasingly important. Loughran and Kulick (LK) noted that often the evidence on the cost-effectiveness of DSM programs comes for utilities themselves. These measurements generally take the form of ex ante engineering studies or ex post measurement. Ex ante engineering studies seek to calculate the potential energy savings a given technology could achieve over currently installed technology. Ex post measurement calculate the change in energy usage through the use of billing data or direct measurement. LK posits that ex post measurements tend to show the ex ante potential energy savings are rarely achieved. They also argue, that traditionally, neither of these techniques account for the fact that many DSM consumers are free riders from the standpoint that such consumers will eventually make such investments absent the DSM program. These new investment are likely to be in technology which embodies improvements in technology[7]. Thus DSM programs likely have a strong temporal dimension. LK cite a 1988 study by Kenneth Train which estimates that about 70 percent of reported energy savings would have occurred in the absences of DSM participation.

LK attempts to account for free riders and test the hypothesis that DSM programs lead to a decrease in energy usage with the following equation.

$$\Delta MWh_{ij} = \quad \gamma_1 IND_{DSM,ij} + \gamma_1 \Delta X_{ij} + \theta_j$$

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[7] Loughran and Kulick, *Demand-Side Management*, 22.

ΔMWh_{ij} represents the change in electric sales for a given utility, "i", within a given State, "j". $IND_{dsm,ij}$ is an indicator variable which reflects whether a utility in a given State had a DSM program. ΔX_{ij} accounts for changes in the number of customers and the proportion of retail electric sales accounted for by industrial and commercial customers. Φ_j accounts for State level changes in Gross State Product (GSP), energy prices, and cooling and heating degree days.

This analysis estimated that for utilities routinely investing in DSM programs, such expenditures lowered electricity sales by between 0.6 and 1.2 percent. By comparison, utilities estimated such DSM expenditures lower electricity sales by between 1.8 and 2.3 percent[8].

LK speaks to other potential bias including the rebound effect, but state that the empirical importance of such effects is not well understood. LK cites Greene, Kahn and Gibson (1999) which estimated the rebound effect reduces potential energy savings from increased automobile efficiency by 20%[9]. Thus the rebound effect, "b", as defined by BC is 20 percent or b=0.20. LK notes that a potential weakness in their approach is its inability to account for, inter alia, rebound effects[10].

In 2008, Auffhammer, Blumstein, and Fowlie (ABF) took issue with two aspects of the LK analysis. The first was the statistic used to test the hypothesis that DSM expenditures increased the energy efficiency of the US economy. ABF argued that one needs to consider the percentage changes in *aggregate* electric consumption due to

[8] Loughran and Kulick, *Demand-Side Management*, 39.
[9] Loughran and Kulick, *Demand-Side Management*, 24-25.
[10] Loughran and Kulick, *Demand-Side Management*, 29.

aggregate expenditures on energy efficiency DSM. LK use average percentage change in electricity consumption due to DSM expenditures across utilities and years as their indicator. ABF argue that this choice of a test statistic underestimates the percent savings of DSM programs and overestimates the costs[11]. Specifically ABF proposes the following modifications to the LK analysis. The S_1 and C_1 variables represent the formulas employed for measuring energy savings and energy efficiency DSM costs respectively. The S_2 and C_2 represent the ABF proposed measures of the same test statistics.

$$\hat{S}_1 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n}\left(\frac{kWh(0)_{nt} - kWh(1)_{nt}}{kWh(0)_{nt}}\right)}{\sum_{n=1}^{N} T_n}$$

$$\hat{S}_2 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n}(kWh(0)_{nt} - kWh(1)_{nt})}{\sum_{n=1}^{N}\sum_{t=1}^{T_n} kWh(0)_{nt}}$$

$$\hat{C}_1 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n} EE_{nt}/\sum_{n=1}^{N} T_n}{\hat{S}_1\left(\sum_{n=1}^{N}\sum_{t=1}^{T_n} kWh(0)_{nt}/\sum_{n=1}^{N} T_n\right)}$$

$$\hat{C}_2 = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T_n} EE_{nt}}{\sum_{n=1}^{N}\sum_{t=1}^{T_n}(kWh(0)_{nt} - kWh(1)_{nt})}$$

ABF also criticize the LK approach for its point estimate approach to hypothesis testing. ABF argue the one must estimate confidence intervals around point estimates of

[11] Maximilian Auffhammer, Carl Blumstein, and Meredith Fowlie, *Demand-Side Management and Energy Efficiency Revisited*, (The Energy Journal, Vol. 29, No. 3, 2008), 93.

energy savings. The null hypothesis tested by LK should only be rejected if one is sufficiently certainly that the observed value would not occur if the hypothesis was true[12].

ABF concludes that the hypothesis the ex post measurements of DSM programs effects, as performed by LK, produce similar results to the reported by utilities cannot be rejected[13].

ABF do not address the other potential biases in the measuring cost-effectiveness of DSM programs.

Gillingham, Newell, and Palmer (GNP) in 2009, distinguish between energy efficiency and energy conservation. Energy consumption may be reduced with or without an increase in energy efficiency, such as is the case with energy conservation. This distinction is important when considers issues such as the rebound effect, whereby the demand for energy services may increase in response to energy efficiency-induced declines in the marginal cost of energy services[14]. GNP defines the energy efficiency market using a production function framework with capital and energy as the inputs. Using such a framework, GNP represents market failures as a divergence of the relative prices used for private decisions from the economically efficient prices. GNP provides a summary of potential market and behavioral failures relating to energy efficiency and

[12] Auffhammer, Blumstein, and Fowlie, DSM Revisited, 100.
[13] Auffhammer, Blumstein, and Fowlie, DSM Revisited, 101-102
[14] Kenneth Gillingham, Richard Newell, and Karen Palmer, *Energy Efficiency Economics and Policy*, (National Bureau of Economic Research Working Paper 15031, 2009), 1-2.

conservation, along with potential policy responses[15]. These are shown in Table I.1 below.

Table I.1
Commonly Cited Market and Behavioral Failures

Potential Market Failures	**Potential Policy Options**
Energy Market Failures	
• Environmental Externalities	Emissions Pricing (Tax, Cap & Trade)
• Average-Cost Pricing	Real-Time and Market Pricing
• Energy Security	Energy Taxations, Strategic Reserves
Capital Market Failures	
• Liquidity Constraints	Financing/Loan Programs
Innovation Market Failures	
• R&D Spillovers	R&D Tax Credits, Public Funding
• Learning-by-Doing Spillovers	Incentives for Early Adoption
Information Problems	
• Lack of Information	Information Programs
• Asymmetric Information	Information Programs
• Principal-Agent Problems	Information Programs
• Learning by Using	Information Programs
Potential Behavior Failures	**Potential Policy Options**
• Prospect Theory	Education and Production Standards
• Bounded Rationality	Education and Production Standards
• Heuristic Decision Making	Education and Production Standards

GNP cite both free-riders and the rebound effect as potential issues which complicate the measurement of energy efficiency policy effectiveness and costs. GNP

[15] Gillingham, Newell, and Palmer, Energy Efficiency Economics, 12.

notes the possible offsetting effect of free-drivers, nonparticipants in DSM programs who are induced to invest in energy efficiency as a result of having observed program participants. Similar to LK, GNP notes that ex ante studies dominate much of the energy efficiency policy. While these studies provide a starting point for understanding and evaluating energy efficiency policy, they do not demonstrate the effectiveness of such policies. Analysis and related literature is shifting to ex post studies to examine the historical effectiveness and cost of energy efficiency policies[16].

GNP cite extensive debate in the literature about the importance of the rebound effect in the context of energy efficiency standards (for a review, see Gillingham et al. 2006), but some empirical evidence suggests it may numerically small in the case of energy efficiency standards (Dumagan & Mount 1993). GNP cites a 2007 study by Small & Van Dender which found a rebound effect of -6%, b=0.06, in the case of clothes washers[17].

GNP also cites the work of LK and ABF discussed above and cites a 2004 study by Gillingham et al. which calculated a cost effectiveness for all DSM programs of $0.034/kWh using only utilities costs and utility reported self-reported savings as compared to the ABF estimate of $0.02/kWh to $0.08/kWh.

Arimura, Li, Newell, and Palmer (ALNP) in 2012, sought to improve the robustness of the LK approach. ALPN propose six changes to the LK methodology[18]:

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[16] Gillingham, Newell, and Palmer, Energy Efficiency Economics, 26.
[17] Gillingham, Newell, and Palmer, Energy Efficiency Economics, 27.
[18] Toshi Arimura, Shanjun Li, Richard Newell, and Karen Palmer, *Cost-Effectiveness of Electricity Energy Efficiency Programs*, (The Energy Journal, Vol. 33, No. 2, 2012), 68.

- Account for possible endogeneity in utility DSM spending
- Augment the data set to include data through 2006
- Incorporate third party DSM spending
- Explore the impact of decoupling regulation
- Calculate confidence intervals similar to ABF
- Model percentage electricity savings as a function of DSM expenditures per customer.

The approach offered by ALNP is unique in its recognition of third-party DSM spending. In the context of their analysis, ALNP identifies third-party DSM spending as that undertaken by state agencies or independent state-chartered energy efficiency agencies, such as the NEO's DSM programs which form the basis for this analysis.

In anticipation of a decline in DSM spending in the wake of electricity restructuring, a number of states established mechanisms to replace utility programs. The most common approach has be to establish a public benefit fund to pay for DSM and other public benefit programs, such as renewable energy promotion, research and development, and low-income assistance[19].

ALNP uses data from the period of 1992 through 2006 in its analysis. ALNP cite specific estimates of the cost-effectiveness of DSM expenditures from prior literature of between 0.9 and 25.7 cents per kWh saved[20]. ALNP conclude that over the 15-year period covered their analysis, DSM expenditures produced an estimate 0.9 percent reduction in electricity consumption within the data period and a 1.8 percent reduction

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[19] Arimura, Li, Newell, and Palmer, Cost-Effectiveness of EEE Programs, 68, 70.

[20] The high end of the range comes from the LK study. ABF argues that rather than $0.258/kWh, LK results show $0.146/kWh when properly weighted.

including estimated reduction that occur beyond the data period. Assuming a discount rate of 5 percent, ALNP estimates an average cost of 5 cents per kWh saved with a 90 percent confidence interval that goes from 0.3 cents to 10 cents per kWh saved[21].

3. Purpose of Paper

This paper focuses on changes in consumer behavior and potential methods to estimate the impact that DSM programs have on consumer behavior, specifically the “rebound effect”. The analysis contained herein seeks an ex post measurement changes in energy usage resulting from DSM expenditures similar to previous work in this field. The approach utilized by ABF regarding the aggregation of results was employed in this analysis.

While many of the previous studies of DSM programs have focused on a macro level analysis, the analysis contained in this paper is conducted at a micro level. BC identify three potential bias in measuring the impact of DSM programs on electric usage. Analysis discussed earlier seeks to account for any free-rider bias. This paper does not explore either potential free-rider or energy price bias but rather focuses solely on estimating the impact of DSM expenditures on customer behavior, i.e. the “rebound” effect. The data included in the analysis only includes “third-party” DSM expenditures encompassed by the NEO’s DSM program. As such the analysis contained herein seeks to estimate the observed behavioral changes of individuals who participated in the NEO’s DSM programs. For purposes of this paper, the definition of EEMs is expanded to

[21] Arimura, Li, Newell, and Palmer, Cost-Effectiveness of EEE Programs, 95.

include all efficiency measures undertaken within the auspices of the NEO's DSM programs, including improving insulation and other efficiency measures.

The methodology proposed by Braithwaite and Caves is used as the starting point for this analysis. In applying the BC methodology, consider the case where a conventional, 78% efficient furnace is replaced with an Energy Star qualified, 90% efficient furnace. Such a replacement is estimated to reduce energy usage by 106 therms annually[22]. Assuming the household did not purchase any other EEMs, then $F^1 - F^0 = 106 - 0 = 106$

Next, in order to derive an estimation of the behavioral response, one would need to measure the actual energy used before and after the introduction of EEMs in a given household. Building on the furnace replacement example above, suppose that prior to the installation of the new furnace, the energy consumption averaged 1,500 therms/year. After installation, because the cost of a unit of heat is not less expensive, the consumer uses more heat. Consequently, average energy usage was reduced to only 1,447 therms per year. Then the observed change in energy usage was $E^0 - E^1 = 1{,}500 - 1{,}465 = 35$. The behavioral change represents the difference between the expected energy savings and observed change in energy usage. This is represented by the *b* term in the equation. Thus in this example, the behavioral impact is equal to

[22] Estimate is based on spreadsheet prepared by U.S. EPA and U.S. DOE downloaded from http://energystar.gov/ia/business/bulk_purchasing/bpsavings_calc/Calc_Furnaces.xls on July 31, 2013.

$$
\begin{aligned}
(E^0 - E^1) &= (F^1 - F^0)(1 - b) \\
(1{,}500 - 1{,}465) &= (106 - 0)(1 - b) \\
35 &= 106(1 - b) \\
b &= 1 - \frac{35}{106} \\
b &= 0.67
\end{aligned}
$$

In this example, for each therm of expected energy savings resulting from the purchase of EEMs, the consumer increases their energy usage by .67 therms, reducing the observed energy savings to 0.33 therms for each therm purchased as EEMs.

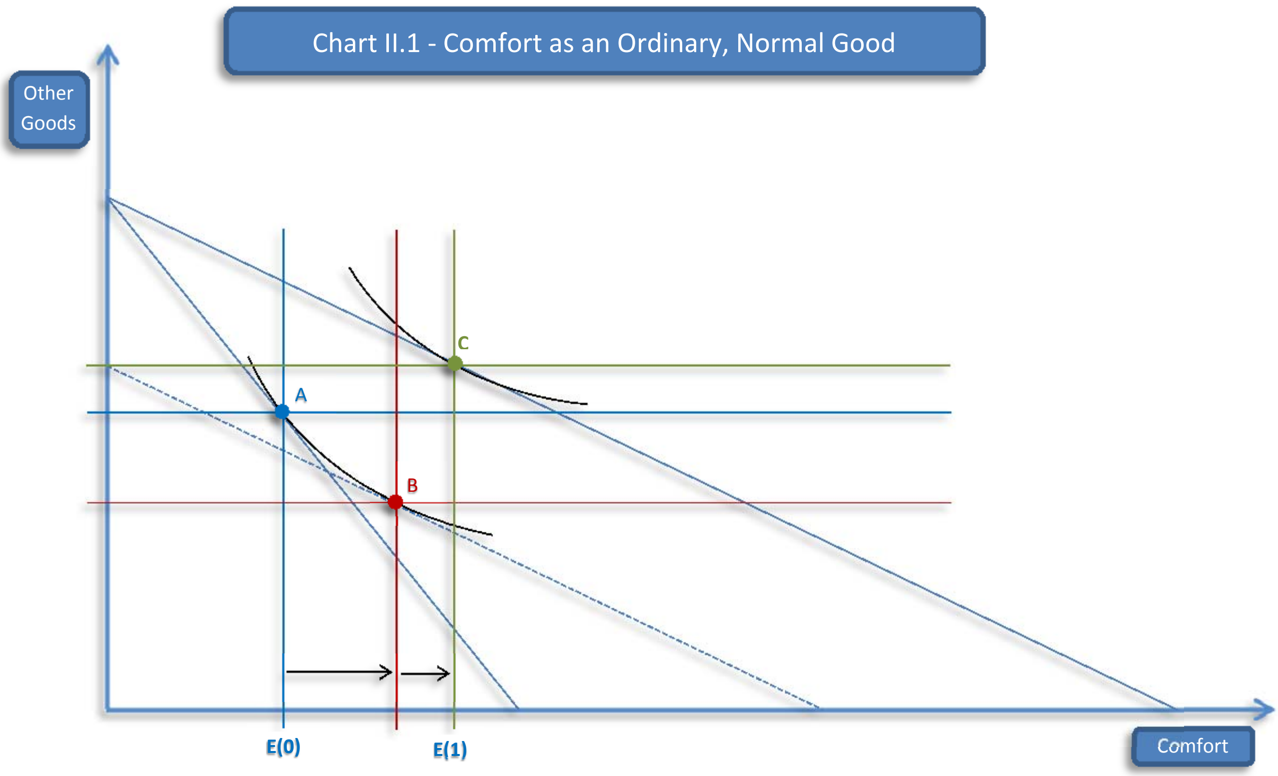
Chapter II - Economic Basis for Behavioral Changes

Next, the economic underpinning of the behavioral response is analyzed. For this purpose, consider a market with two goods where Good 1 represents consumer purchases of comfort and Good 2 represents purchases of all other goods and services. The direct effect of DSM programs is to reduce the price of comfort through the purchase of EEMs. All else remaining constant, after an EEM purchase, a consumer will use less energy to maintain a given level of comfort. Consider a person who desires to maintain a temperature of 74 degrees in their house during the summer. Prior to the EEM purchase, the individual spent $80 per month to maintain this level of comfort. After the EEM purchase, the individual may only need to spend $76 per month to maintain the same level of comfort[23]. Thus the price for comfort for this individual has been reduced by $4/month.

Micro-economics decomposes the effects of changes in price into substitution effects and income effects. The substitution effect is the change in demand which results from the change in the rate of exchange between goods. A price reduction in comfort changes the rate of exchange between comfort and all other goods. In economic theory, the substitution effect is proven to be negative, meaning that the demand response is the opposite sign of the price change. In our case, the price for comfort is reduced and therefore the substitution effect associated with such a price decrease will cause demand for comfort to increase.

The income effect is the change in demand resulting from the individual having more purchasing power. The sign of the income effect can be either positive or negative. A price decrease for a given good results in an additional amount of income being available to purchase all goods. For a normal good, the sign of income effect is positive, meaning that the response to the increase in income which results from a price decrease for comfort increases the consumption of comfort. Such effects are shown on the following charts.

[23] Example based on 1,000 kWh/month prior to EEM and 950 kWh/month after EEM, with an electric rate of $0.08/kWh.



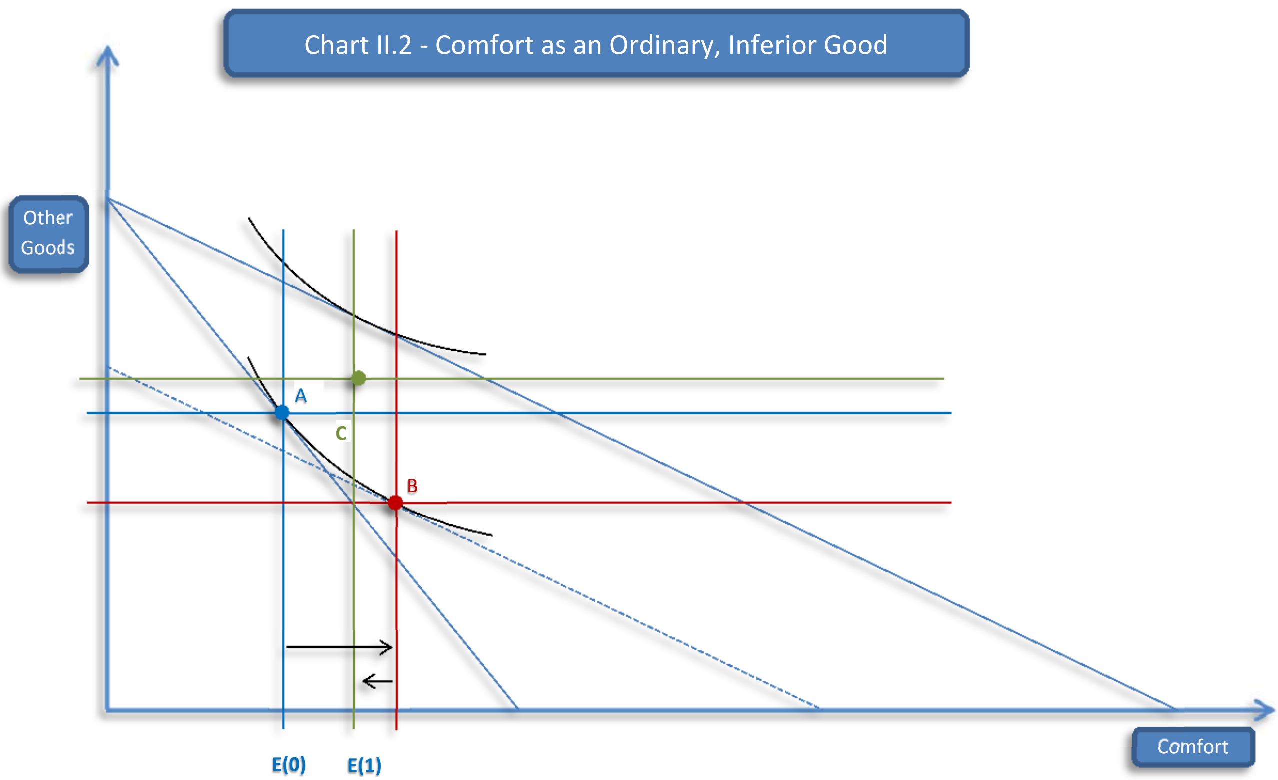
As shown in Chart II.1, in the case where comfort is an ordinary, *normal* good[24], the substitution effect of the price decrease for comfort increases demand for comfort from point A to point B. The income effect further increases demand for comfort from B to C. Thus in the context of comfort, demand increases from $E(0)$ to $E(1)$.

In the case where comfort is an ordinary, *inferior* good[25], the sign of the income effect is negative which results in a reduction in the demand for comfort as income increases. This is shown on Chart II.2, below. The substitution effect of the price decrease for comfort increases demand for comfort from point A to point B, while the

[24] An ordinary good is a commodity for which more of the good is demand when the price for the good is reduced. A normal good is a commodity for which more of the good is demanded when income increases.

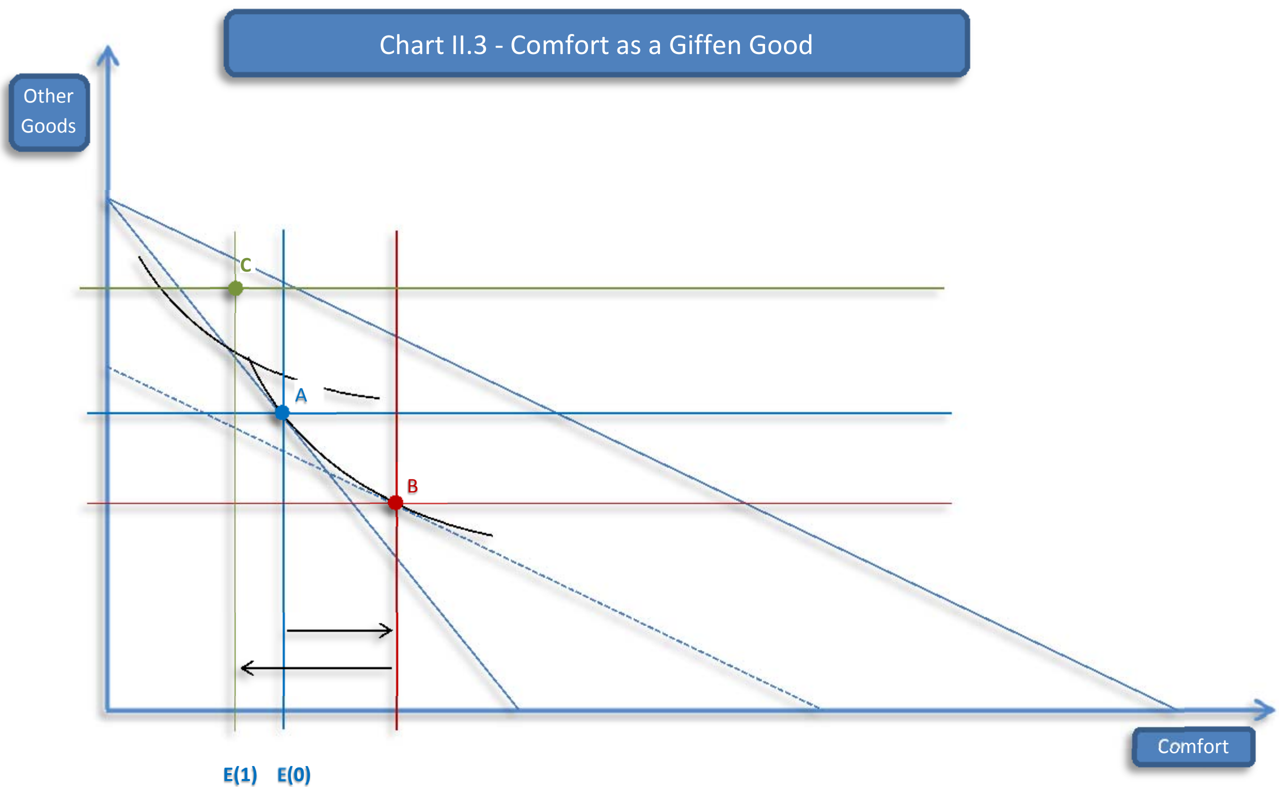
[25] An inferior good is a commodity for which an increase in income results in a reduction in the consumption of the good.

income effect decreases demand for comfort from point B to point C. This effect is shown on Chart II.2. For the purposes of this analysis, the behavioral response encompasses both substitute and income effects. In the case of an ordinary good, the substitution effect will always be greater than any counter-acting effects resulting from the change in income. Thus, the behavioral response will still result in increased demand for comfort.



A "Giffen" good is a special case where a price decrease for a good actually results in a decrease in demand for the good. In such a case, the income effect is negative and greater in magnitude that the substitution effect. An example of this is shown in Chart II.3. The substitution effect again increases demand for comport from Point A to

Point B, while the income effect decreases demand for comfort from Point B to Point C. In the case of a Giffen good, the consumer demands less comfort than they did prior to the price decrease for comfort.



One would expect comfort would generally be an ordinary, normal good and that price decreases and income increases will both have positive impact on demand for comfort.

The primary means by which consumer purchase comfort is through their demand for electricity and natural gas. For the purpose of the analyses contained in this paper, the purchase of these energy products will be used as a surrogate for comfort demand. The economic theory of how consumers respond to price reductions has implications for the measurement of the effectiveness of DSM programs, generally. One cannot simply look at expected energy savings when measuring the effectiveness of investments in DSM programs. As noted by Braithwaite and Caves, the behavioral response of consumers is an integral part of such analyses. Further, such behavioral responses could have implications on the design of DSM programs. In this paper we will explore two main questions.

- Does the observed behavioral impact appear to differ based on the income level of the consumer by estimating whether the observed behavioral responses differ between the weatherization and loan programs?
- Does each additional dollar of DSM investments have the same impact on consumer behavior?

As discussed earlier, the level and type of information available does not lend itself to a straight-forward calculation. As such, econometric techniques were employed to estimate the amount of EEMs purchased as well as the changes in energy usage and the related behavioral changes. The econometric techniques employed were driven based upon the available project information. This consisted of a four step process, 1) data collection and processing, 2) estimating the change in energy usage, 3) estimating the amount of EEMs purchased and 4) deriving the estimated behavioral impact.

Chapter III - Description of Project

At its heart, the BC methodology is a relatively straight-forward analysis. Identify the expected change in energy usage resulting from the purchase of EEMs, F^1 -

F^0, and the actual change in energy usage, $E^0 – E^1$. The difference between these two measures then represents the behavioral changes or rebound effect.

Unfortunately, the available data does not lend itself to such a straight-forward analysis. First, NEO records during the study period did not contain the level of detail which would allow the capturing of the precise amounts of EEMs that have been provided to participants in the NEO's DSM programs. Such data would provide a measure of the expected change in energy usage, $F^1 - F^0$. Specifically, while the NEO records contained the dollar amounts expended, the records did not contain information on the specific type of appliance replacements or other energy savings measures, such a 75% efficient furnace was replaced with a 95% efficient furnace.

Further, it was difficult to ascertain if participants purchased additional EEMs outside of the NEO's DSM programs. Often, there was not a precise date of when the EEMs were put in place as a series of EEMs were often put in place over a period of several weeks. This presented difficulties in measures that actual change that occurred in energy usage, $E^0 – E^1$.

Given such, a two-step analytical process is proposed. Under the first-step, Phase 1, econometric techniques will be employed to estimate the actual change in energy usage, $E^0 – E^1$. Similar to previous work in the DSM field, a series of factors are used to account for changes in energy demand not associated with EEM purchase, including economic activity, energy prices, and weather conditions.

Under Phase 2 of this analysis, additional econometric techniques will be used to disaggregate the estimates of actual energy usage changes in to estimates of the expected energy usage changes, $F^1 - F^0$, and the rebound effect, b.

Chapter IV - Data Collection and Processing

1. Project and Energy Data Collection

a. Selecting a Sample Period

In order to perform the analysis, energy usage data needed to be obtained from periods both before and after the DSM projects were undertaken. Given the cyclical nature of heating and cooling needs, a minimum of 12 months of energy usage was required from before and after the DSM investment. Since the usage data were collected from the utilities, this study was dependent upon their record-keeping to acquire historical usage amounts. Utilities across the state varied in the amount of historical data they collected and retained. Consequently, the impacts of loan and weatherization projects undertaken during the year 2009 were examined. This allowed the use of data from calendar year 2008 as the pre-project period and data from calendar 2010 as the post-project period.

b. Project Data Collection

For this analysis, a project is considered to be a completed loan or weatherization application related to a particular property.

Data from the Weatherization Assistance program were obtained manually. Each participating non-profit agency was required to file a Batch Control Job Order (BCJO) in order to receive reimbursement from the Weatherization Assistance program. The BCJO generally contains the participant's name, location information, building type, ownership, funding source, date information, and summary of EEM investment amounts. However, the BCJOs during the sample period did not contain detailed information as to the specific EEMs which were employed both in terms of the existing appliances and energy saving measures as well as their respective replacements or improvements. As such, econometric techniques were employed to estimate the EEMs purchased based upon dollars invested in specific categories of investment.

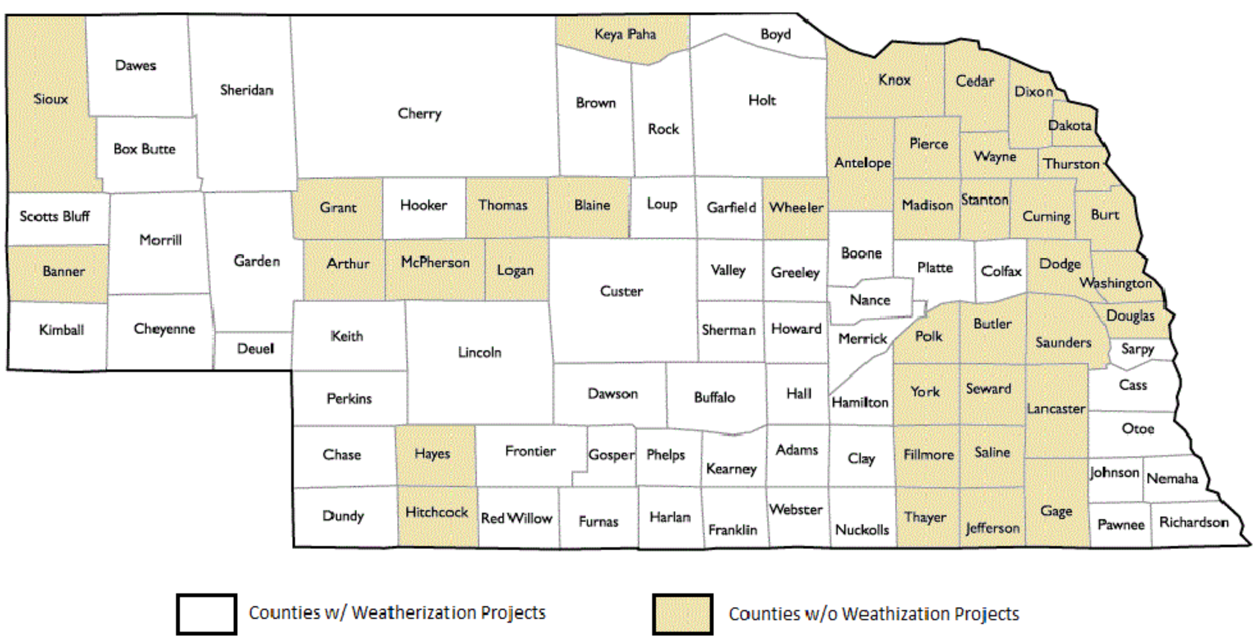
During the analysis period, while most funding requests included a standard summary page, the supporting documents were in large part unique to each participating agency and varied greatly from agency to agency. A significant amount of time was devoted to review and interpretation of the filed supporting documentation, in an effort to ensure comparable categorization of investments between agencies.

The NEO staff provided all BCJOs which were submitted for payment during 2009 and 2010. BCJOs from the four non-profit agencies that were not part of our analysis were excluded and not reviewed. If the BCJO or supporting documentation indicated that all or a majority of the work was not performed during the January 2009 through December 2009 time frame, the project was excluded. If further examination indicated that the primary heating source for the residence was not electricity or natural gas, the project was excluded from the analysis.

In total, information on 835 projects was obtained. The investment data collected from these weatherization projects encompassed 54 of the 93 counties within Nebraska as shown in the map in Figure 1 below. As discussed earlier, this project only encompassed five of the nine non-profit organizations which provide services through the NEO's weatherization program. The 54 counties served by the five providers included the study account for 67% of the total land area in the state, but only for 38% of the population. In many cases, the other 39 counties were provided weatherization services through the four non-profit agencies not included in this analysis.

Figure IV.1

Map of Counties Providing Weatherization Data



For projects included in our analysis, energy improvements were assigned into the following 12 categories:

- Air Infiltration
- Windows
- Doors
- Insulation
- Other HVAC
- Air Conditioning
- Furnace
- Hot Water Heater
- Lighting
- Safety
- Unallocated Labor
- Miscellaneous

Costs pertaining to both material and labor were collected for each type of improvement. To the extent labor costs or miscellaneous expenses were not allocated to a specific investment category, efforts were undertaken to assign those costs to the relevant cost categories. In the event that project information did not contain adequate data with which to make an accurate assignment of unallocated labor costs, those values were assigned to the "Unallocated Labor" category. Expenditures that were undertaken solely for health and safety concerns and deemed unlikely to result in energy efficiency gains were assigned to the "Miscellaneous" category.[26]

Information about loan projects undertaken during the sample period was developed in cooperation with the state data center. The only information available regarding effective date of DSM investments for the NEO's loan projects was the "NEO Participation" date which was the date the NEO provided notice that the project was eligible for a loan. NEO staff indicated that in some instances the work on a loan project may not have been completed for six to 12 months after the NEO participation date. Also, in some cases projects were approved while work was on-going or even after being completed. Based on this information, we extracted data with "NEO Participation dates"

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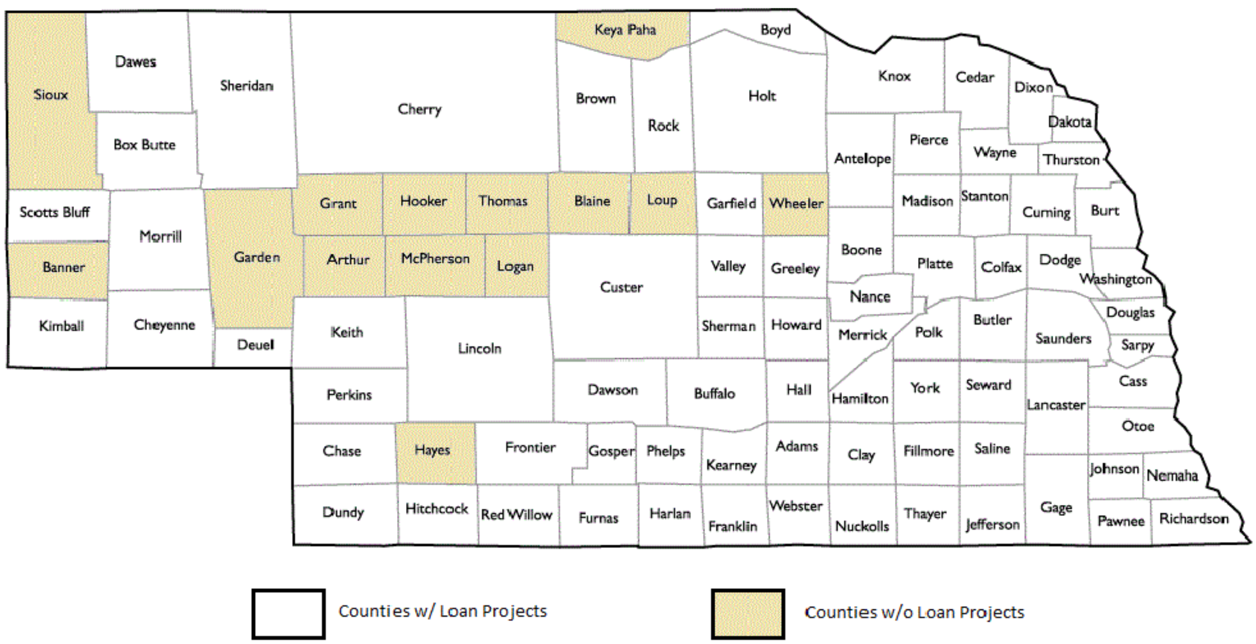
[26] A total of $38,678 from 105 projects was assigned to the "Unallocated Labor" category. A total of $27,330 from 291 projects was assigned to the "Miscellaneous" category. These amounts represent 2.0% and 1.4%, respectively, of the total investments identified for the five agencies during our analysis period.

from between 7/1/2008 through 3/31/2010. The survey process discussed later in this document was used to eliminate projects that did not occur during the sample period.

Investment and other data from the Energy Loan Program were obtained electronically. Four databases were accessed to obtain relevant data on the loan program. The "Loan Summary" database contained the date the project was approved by the NEO. The "Project Summary" database contained data on the location of the project, the congressional and legislative districts, and total project expenditure amounts. The "ECM" database contained data on the specific types of improvements which were made under each project. The "Fuel Supplier" database contained data pursuant to the electrical and natural gas providers for each project. The data obtained from each of these databases was combined based on the unique loan identification number assigned to each project. Similar to the weatherization projects, projects that indicated they had heating sources other than electric or natural gas were excluded.

A total of 984 records were obtained and 120 different classes of improvements were identified. In some cases, an individual property had more than one loan project undertaken. These projects were consolidated and a single property file was created. The data from the loan program encompasses 79 of Nebraska's 93 counties as shown in the map in Figure 2 below. It is worth noting that 11 of the 14 counties that did not receive any funding from the Energy Loan Program also did not receive Weatherization Assistance Program funding from the five non-profit agencies included in this analysis. While weatherization services in these areas may have been provided by a non-profit agency not included in the study, it may be beneficial to follow-up with public education in these counties to make sure that residents are aware of the Weatherization Assistance and Energy Loan programs.

Figure IV.2
Map of Counties with Loan Data



In total, information on DSM investments for 1,819 properties was obtained -- 984 unique properties that had at least one loan project undertaken and another 835 unique properties that had at least one weatherization project undertaken. As shown in Table IV.1 below, four loan properties had more than one loan. Each weatherization project was unique.

Table IV.1

Breakdown of Energy Loan and Weatherization Projects and Properties

	Energy Loan	Weatherization	Total
Projects	988	835	1,823
Properties	984	835	1,819

To create consistent analysis across programs, the 12 Weatherization Assistance Program categories and 120 Energy Loan program categories were combined into a total of 10 investment categories. Table IV.2 below shows the categories of energy improvements considered and briefly describes improvements included in each category.

Table IV.2

Types of Energy Improvements

Type	Description
Air Conditioning	New air conditioning units and repairs to existing units, including related labor costs.
Doors & Windows	Replacement of existing doors & windows, addition of storm doors & windows, repair of existing doors and windows, weather stripping, and repair of existing walls for air infiltration purposes, including related labor costs
Furnace	New furnace units and repair to existing units, including related labor costs.
Heat Pump	Addition of new heat pumps and replacement of existing heat pumps, including related labor costs.
Hot Water Heater	New hot water heaters and repair of existing hot water heaters, including related labor costs.
HVAC Other	Repair to existing ducts system, including related labor costs.
Insulation	Addition of new insulation and replacement of existing insulation, including related labor costs
Lighting	Replacement of existing light bulbs with CFLs.
Miscellaneous	Health and Safety improvements and other non-energy efficiency investments such as pressure testing, and unallocated labor costs.
Other Appliances	Appliances such as refrigerators, dishwashers, clothes washers, freezers, and fireplace inserts.

Table IV.3 below breaks down the number of properties and total investments for each type of improvement by weatherization and loan program. Air conditioning, heat pumps, and other appliances were almost exclusively financed under the loan program. Insulation, lighting and miscellaneous investments were almost exclusively the domain of the weatherization program. While the five other types of investments were undertaken by both programs, weatherization had more in each category.

Table IV.3

Number of Properties with Each Type of Improvement

Improvement Type	Loan		Weatherization	
	Count	Investment	Count	Investment
Air Conditioner	131	$412,540	2	$5,397
Doors & Windows	389	$3,782,954	754	$637,967
Furnace	306	$1,096,411	413	$594,345
Heat Pump	342	$2,400,988	---	---
Hot Water Heater	46	$50,558	225	$66,794
HVAC - Other	287	$67,805	645	$34,604
Insulation	30	$238,063	691	$543,086
Lighting	---	---	676	$10,886
Miscellaneous	44	$11,203	562	$87,097
Other Appliances	8	$16,711	---	---
Total	929	$8,077,233	822	$1,980,176

Table IV.4 below breaks down the average dollar value of the investment in each type of improvement per improved property by Energy Loan and Weatherization Assistance programs. The average investment per improved property was larger for the loan program as compared to the weatherization. Of particular note are the doors & windows and insulation categories where the average investment for loan projects was more than 10 times greater than the average investment for weatherization projects.

Table IV.4

Average Investment per Improved Property

Type	Loan	Weatherization
Furnace	$3,583	$1,439
Hot Water Heater	$1,099	$297
Heat Pump	$7,020	---
Air Conditioner	$3,149	$2,699
Other Appliances	$2,089	---
Doors & Windows	$9,725	$846
HVAC	$236	$54
Insulation	$7,935	$786
Lighting	---	$16
Miscellaneous	$255	$155
Average per Property	$8,695	2,409

c. Authorization Forms

In order to participate in either the Weatherization Assistance or Energy Loan programs, an applicant must sign a form authorizing their energy provider(s) to release requested billing information to the NEO or authorized parties. These authorization forms are retained only in the form of paper copies. The authorization forms for the Energy Loan Program were retained on-site at the NEO. For some of the Weatherization Assistance projects, the authorization forms were included with the supporting information attached to the BCJO. For the remainder of the projects, the authorization forms were retained by participating non-profit agency. Paper copies were made of the authorization forms which were on-site at the NEO. The participating non-profit agencies were contacted and paper copies were obtained of the authorization forms which were not on-site at the NEO. The paper copies were scanned into Adobe PDF files for each participating project.

d. Energy Data Collection

Many of the projects did not contain information which identified the name of the electric and natural gas energy providers. Further, a cursory review indicated that not all energy providers contained in the records were accurate. Consequently, a review of energy provider service territories was undertaken. Each property was assigned to up to three possible electrical providers and two possible natural gas providers based upon energy providers' defined service territories. Each property address was then sent to its assigned possible electrical and natural gas providers. The authorization forms associated with each project were sent to the energy providers, if requested. Each utility was asked to provide monthly data for properties that they served. The data requested spanned the period from 2008 through the latest date available. The requested data included:

- Customer name
- Meter Read Date
- Unit of Measure
- Service Address
- Billing Period
- Charge for Usage
- Days in Billing Period
- Usage during Billing Period
- Actual or Estimated Usage

A total of 1,120 electrical records and 922 natural gas records were received from the energy providers. The majority of these responses were received electronically in the form of Excel spreadsheets. The spreadsheets were formatted in a consistent manner and then the electric records were aggregated into a single file as were the natural gas records.

The responses which were not received electronically or in Excel format were hand entered into the appropriate electric and natural gas aggregated files.

These records were then checked for accuracy. Five tests were performed on the records received from the utilities in an effort to ensure their accuracy before the records were processed further.

1. **Test of pre-investment data.** The earliest billing period for each property was identified. If the earliest billing period occurred after January 2008, the property was excluded. The test was designed to ensure that enough utility billing information was available to measure reasonably pre-improvement usage. In addition, if the earliest billing period was prior to January 2005, the property was excluded. This additional test was designed to identify billing information that did not contain a valid date[27].

2. **Test of post-investment data.** Next the latest billing period for each property was identified. If the latest billing period was before December 2010, the property was excluded. This test was designed to ensure that enough utility billing information was available to measure reasonably post-improvement usage. Further, if the value associated with the latest billing period was greater than October 2011, the property was also excluded. This test was also

[27] Excel stores dates as a numeric value. The number zero corresponds to the date of January 1, 1900 date. Each additional whole number represents one day. Accordingly, the number one represents the date of January 2, 1900. Accordingly, if a date filed was left blank, Excel would interpret the zero value as a date of January 1, 1900. If a usage value of 100 was inadvertently entered in the date field, Excel would interpret the value of April 9, 1900. By eliminating records with dates prior to January 2005, the review of the provided billing information attempted to eliminate these possible types of errors.

designed to ensure that the billing information contained valid date values. The use of the October 2011 date value coupled with the January 2005 date value from Step 1 was designed to identify properties which likely contained inaccurate billing date information[28].

3. **<u>Test for billing periods.</u>** The number of billing periods provided for each property was compared to the estimated number of months between the earliest and latest billing dates identified in the two previous steps. If the count was not within one billing period of the estimated number of months, then the property was excluded. This test was designed to ensure that for each property, on average, there was one billing record per month.

4. **<u>Test for number of days.</u>** The total number of days included in the billing information for each project was compared to the number of days between the earliest and latest dates calculated in the first two steps. If the variance between the two values was greater than two percent, the property was excluded. This was designed to validate further overall accuracy of the information provided for a given property.

5. **<u>Name test.</u>** The data was checked to see if more than one name appeared in the billing information for each property. If more than one name was found the property was excluded. This was done in an effort to determine if a change in resident had occurred at the property.

[28] As discussed earlier, Excel stores dates as numeric values. January 1, 2005 is represented by the value of 38,353 and October 2011 by the value 40,847. Accordingly, properties with billing records containing values in the billing date field outside of the range of these two values were excluded. Properties with blanks date fields or other values which were inaccurately placed in the date field were also excluded.

As a result of these tests, 636 electrical records were determined to be valid: approximately 57 percent of the 1,120 records received. Of the 636 electrical records, 477 of these records were derived from actual meter readings, while the remaining 159 records were based, at least in part, on billing estimates. For natural gas, 404 records were determined to be valid: approximately 44 percent of the 922 records received. Of the 404 records, 310 of these records were derived from actual meter readings, while the remaining 94 records were based, at least in part, on billing estimates.

To create a symmetric property panel, the monthly billing records for each property were examined in order to ascertain that there were 36 billing records, generally for the period of January 2008 through December 2010.

1. The first step was to determine if there was a billing record for January 2008. In an effort to deal with the various billing cycles and periods, the billing information for each property was first examined to determine if it contained a billing record that began in the first half of January 2008, then the second half of December 2007, then the second half of January 2008, and then the first half of December 2007. The first identified billing period date was then used as the starting date for the panel data of a given property. If a date within the four discrete periods described above could not be identified then the property was excluded from the analysis.
2. Next, given the requirement for 36 consecutive monthly billing records, the data was examined to determine if 36 billing period records existed between the starting date from the previous step and from a date 36, 35, or 37 months

later. Similar to the previous step, billing records for a property were examined to determine if a billing record existed for the first half of the month 36 months from the first date, the second half of the month 36 months from the first date, the first half of the month 35 months from the first date, the second half of the month 35 months from the first date, the first half of the month 37 months from the first date, and the second half of the month 37 months from the first date. Next, to the extent a valid date was identified for any of these six periods, the number of monthly billing records was counted for each property from the starting date through the potential end date. If there were 36 billing records between the first date and identified date, then that date was used as the last date for the purposes of identifying 36 periods of billing information for use in the panel analysis. If a billing record could not be identified within the six date periods described above or if none of the six possible last dates resulted in a count of 36 monthly billing records, the property was excluded from the analysis.

As a result of this process, 29 electrical and 58 natural gas records were eliminated.

2. Program Participant Surveys

The purpose of this part of the evaluation was to identify households that had participated in the Nebraska Energy Office NEO Energy Loan and Weatherization Assistance programs and that had made no additional substantial changes which would likely affect energy usage. To do this, as many households as possible that participated in the Energy Loan and Weatherization Assistance programs in 2009 were surveyed. Each participating household was asked about improvements, modifications and/or additions that may have made to their home or household during the 2008 to 2010 time period.

a. Design and Item Selection

The Nebraska Energy Loan and Weatherization Surveys were designed to meet the data needs for the evaluation of the program. Two separate, but similar, surveys were created: one for those households which received weatherization grants and one for those households which took out an energy loan.

Literature reviews were conducted to identify household and structure changes that could impact energy consumption by households and businesses such as the purchase of new appliances or installing additional insulation. Although there are many changes that could affect energy usage, interest focused on identifying changes that have a substantial impact. Experts at the Nebraska Energy Office reviewed the universe of possible energy changes and selected those most likely to have a substantial impact. The following modifications were selected:

1. Replacement furnace
2. Replacement central air conditioning or install new central air
3. Replacement heat pump or install new heat pump
4. Replacement water heater
5. Install additional window air conditioners
6. Install addition of insulation to walls, ceiling, attic, or crawl space
7. Replacement windows and doors throughout the structure

8. Replacement lighting throughout the structure
9. Replacement of stove, oven or clothes dryer if changing fuel source
10. Addition or subtraction of fireplace or heating stove
11. Addition or subtraction of a hot tub or Jacuzzi
12. Major home additions or changes (e.g., heating garage, adding a room)
13. Gas or electricity disconnected or heating/cooling not working for more than one week
14. Additions/subtractions to the number of people occupying the structure
15. Change in the amount of time when the structure was occupied or vacant
16. Other changes that may have substantially changed energy usage

Questions were constructed for the survey to assess if any of the 16 types of changes occurred a year prior to or after the modification funded through the Nebraska Energy Office. In addition to questions about changes affecting energy usage, questions were included to determine the type of structure (e.g., single family dwelling, mobile home, apartment), whether the occupant rented or owned the building, whether propane was used as a fuel source, the names of their utility companies, how likely residents would have been to make energy improvements without assistance, and whether the energy loan or grant caused residents to make other changes to improve energy efficiency.

After each survey was drafted, the interview schedule was programmed on the computer and piloted. For piloting, interviewers were instructed to be particularly observant for problems in wording, item ordering, and skip patterns. Following the pilot interviews, a debriefing discussion was held with the interviewers to go over the schedule and to discuss problems encountered and reactions to the interview. Pilot interviews were completed by professional interviewers, all by telephone. The results of the pilot interviews and any necessary changes to the interview schedule were incorporated in the final instrument.

b. Schedule Construction

The Computer Assisted Telephone Interviewing (CATI) system was used for the data collection. Development of the interview schedule on the CATI system required that all of the question items be entered on the computer. Next, instructions were prepared for each item, indicating its position in the interview, skip patterns, and appropriate response categories. An advantage of the CATI system is that the interviewer's task remains simple, regardless of the complexity of the interview. The computer makes the decisions about question ordering and skips patterns on the basis of the responses to earlier items.

c. The Sample

The list of participants in both the Energy Loan and Weatherization Assistance programs was developed from the previously described data. Any person on the list without a valid phone number was placed into a “tracking” file (or locating file) so that a staff member could attempt to locate a valid phone number. Multiple attempts to locate a phone number were tried using free services available via the Internet.

d. Interviewer Training, Supervision, and Quality Control

The interviewing was completed by professional interviewers. All of the interviewers had previous experience in telephone interviewing; several were highly skilled with many years of interviewing experience. Interviewers were supervised by permanent staff.

Training for the interviewers involved two steps. First, the study director and permanent staff met all interviewers and discussed in detail the schedule and the procedures to be used. The interviewers were trained to use the Computer Assisted Telephone Interviewing (CATI) techniques and spent several hours of practice time becoming accustomed to using CATI. Each interviewer was given a short instruction manual which they were instructed to read carefully and which they were required to bring with them each time they interviewed. Second, all new interviewers were required to complete practice interviews. These practice interviews were carefully examined by staff for errors, inadequate records on open-ended questions, and the like. All interviewing was done in interviewing lab and offices. Supervisory staff was available during calling hours to supervise the interviewing and to answer questions.

The proximity of interviewer workstations, as well as the use of telephone monitoring equipment, provided opportunities for careful supervision as the data was collected. The study director and others on staff were always accessible so that questions from the interviewers could be handled immediately and, if necessary, the respondent could be called back. Further, supervisors regularly monitored interviews while they were being conducted. This helped to identify interviewing problems and difficulties. Interviews were very carefully edited by the staff. This was done on a regular basis so that errors could immediately be brought to the attention of the interviewers and corrected. If answers were recorded incorrectly or in an incomplete manner, the interviewer was asked to call the respondent back and correct the error.

The interviewing staff was paid by the hour, not by the number of interviews completed. This method of payment was used to ensure the high quality of the data collected. The progress and productivity level of each interviewer, however, was monitored to detect problems in the method of interviewing. Various rates were calculated to reflect the completion rate per hour, the total number of attempts per hour, a refusal rate, etc., to monitor the progress of each interviewer compared to the entire group of interviewers. Individual attention was given if an interviewer's rates strayed from the overall mean.

e. The Interviewing Process

A few business days prior to phone calls, an advance letter was sent to households in the sample. The letter informed respondents about the impending survey phone call and provided information about the survey in order to help increase our completion rate.

In order to make certain that respondents could be reached at a time when they were available to complete the survey, multiple attempts were made to reach each person in the sample at varying days and times including daytime, evenings, and weekends. Additionally, interviewers were instructed to leave a voicemail or message after five or more attempts when possible.

The data were collected from April 13, 2011 until July 27, 2011. Table IV.5 displays the final outcome for all respondents in the sample by program type. The first column in Table IV.5 shows that interviews were completed with a total of 1,173 respondents: 754 households from the Energy Loan program and 419 households from the Weatherization Assistance Program. Comparing these to the total number of interviews attempted (column (7) of Table IV.5), the overall response rate for the Energy Loan program was 81 percent. The response rate for the Weatherization Assistance Program was 51 percent. The response rate as a whole was 67 percent.

Table IV.5

Survey Results

Program	(1) Completed Interviews	(2) Refusal	(3) Non-Trackable - Attempt	(4) Non-Trackable - No Phone	(5) Non-Complete	(6) Ineligible (did not participate in program or deceased respondent)	(7) Total
Loan	754	35	90	0	42	6	927
Weatherization	419	56	208	70	55	11	819
Total	1,173	91	298	70	97	17	1,746

Column (2) of Table IV.5 shows the number of respondents who refused an interview. They totaled about five percent of the sample. Column (3) entitled 'Non-Trackable - Attempt' indicates the number of records where a phone number was attempted, but it was either a wrong number or disconnected and we were unable to locate another working number. In total, they accounted for about 17 percent of the entire sample. However, they accounted for 25 percent of the weatherization sample. Column (4) entitled 'Non-Trackable - No Phone' indicates the number of records where no phone number was found; therefore no call attempt was completed. All of these were for the Weatherization Assistance Program.

The 'Non-Complete' column indicates the number of records where an interview was not completed prior to the end of the study (i.e. the last disposition was a no answer, answering machine, callback, etc.) The 'Ineligible' column indicates the number of records where the respondent claimed they did not participate in the program or the respondent was deceased. Combining columns (3) through (6), almost 15 percent of the households who participated in the loan program during 2009 were unreachable by 2011 while more than 40 percent of weatherization participants were unreachable.

f. Processing of Completed Interviews

Completed interviews were carefully processed and recorded by the staff to ensure that each interview was accounted for and its progress along the various steps of editing, coding, merging, and uploading could be monitored. As previously mentioned, interviews were conducted using CATI software which saves responses on a networked file server. Each day, automatic backups were made of all directories containing information relevant to the survey, and the responses (both numeric and open-ended) were scanned for apparent errors or problems by the staff. Because the data was directly entered on the computer at the time of the interview in computer-readable form, no additional data entry steps were needed. The open-ended data were edited and spell-checked for typographical errors, then sorted and merged.

g. Loan Results

There were 754 complete interviews for the Energy Loan Program. All 754 confirmed they were the recipient of the loan. When asked if they lived or owned the home at the address in question, all confirmed they did. However, some corrected the address. Others indicated they lived at the address but the loan was for a rental unit at another address. Others clarified the time they lived in the home. Some moved in less than a year prior to the improvement and some moved out of the home within a year after the improvement. The large majority of homes were detached single family homes (97%) with a few mobile homes, duplexes, apartments, and other types of homes.

A series of questions was asked pertaining to energy improvements the respondent had made and whether those improvements were part of the loan program. Some of those questions searched for consistence between the survey answers and the data gathered from the loan program itself. These questions related to heat pumps, furnaces, air conditioners, insulation, water heaters, window and door replacement, lighting, and other appliances and HVAC. Other questions asked if the entire project was funded by the loan program or if other funds were used as well.

Another series of questions related to other changes in the dwelling or household composition that would influence energy consumption independent of any energy improvements financed by the loan program. These included questions about the addition or subtraction of fireplaces, heating stoves, hot tubs, Jacuzzis. There were questions that asked about major home additions or changes. Other questions explored changes in usage due to shutting off utilities, adding or subtracting people living in the dwelling, substantial changes in the time that the dwelling was occupied, or any other types of major changes that would affect energy usage.

Results from the survey indicate that 495 properties had to be excluded from the first stage analysis based on survey results. The main reasons for exclusion were that the project was not funded entirely through the loan or there was a significant change in energy usage, the dwelling or the household. There were approximately 232 properties excluded from the initial analysis (almost half of the exclusions) solely because not all of the energy improvement was financed through the loan program. Another 104 (21 percent) were excluded from the initial analysis solely because of a significant change in energy usage, the dwelling or the household. Another 115 were excluded for both reasons. The remaining 44 were excluded for other reasons.

The excluded properties were not included in the statistical analysis to develop parameters that explain energy saving as a function of the investment. They were, however, included when we quantified the overall impact of all improvements made during the sample period.

h. Weatherization Results

There were 419 complete interviews for the Weatherization Assistance program. All 419 confirmed they were the recipient of the assistance. When asked if they lived or owned the home at the address in question, all confirmed they did. However, some corrected the address. Others indicated they lived at the address but the loan was for a rental unit at another address. Others clarified the time they lived in the home. Some moved in less than a year prior to the improvement and some moved out of the home within a year after the improvement. The large majority of homes were detached single family homes (86%) with 11 percent living in mobile homes and a few living in duplexes, apartments, and other types of homes.

Results from the survey indicate that 196 properties had to be excluded from the first stage analysis based on survey results. More than half were excluded because there was a significant change in energy usage, the dwelling or the household. Only a quarter were excluded from the initial analysis solely because not all of the energy improvement was financed through the Weatherization Assistance Program. The remaining households were excluded for other reasons.

Energy Loan and Weatherization Assistance Program survey results are summarized in Table IV.6, below.

Table IV.6

Number of Properties with Useable Energy Data

	Electricity			Natural Gas		
	Total	Loan	Wx	Total	Loan	Wx
Received data from Energy Provider	1,120			922		
Valid data	636			404		
Consecutive 36 month panel	607	381	226	346	228	118
Residential and Meets Survey Standards	339	181	158	187	102	85

3. Explanatory Parameters

Next we sought to identify the various factors which generally influence either electric or natural gas usage, or both. When estimating the change in energy usage which results from the purchase of EEMs, one cannot simply review energy bills and subtract pre-EEM energy usage from post-EEM energy usage to determine the difference. Factors such a daily temperatures and energy prices will also influence energy usage. For example, the year preceding the purchase of EEMs may have been significantly warmer than the following year such a purchase. This would tend to increase cooling needs while reducing heating needs from one year to the next. As such, a simple comparison of usage between the two periods would not be limited to impact of the EEMs.

To this end, the following categories of potential explanatory variables were identified:

Table IV.7

List of Explanatory Variables

Category	Description
Constant	Accounts for the impact of factors other than those described below.
Energy Prices	Accounts for changes in the price consumers pay for energy.
Income Levels	Accounts for change in consumer income.
Cooling Degree Days (CDDs)	CDDs are the standard measure of the impact which temperature has on the use of cooling sources.
Heating Degree Days (HDDs)	HDDs are the standard measure of the impact which temperature has on the use of heat sources.
Trend	Accounts for normal changes in consumers' energy usage over time and correlation between observations[29].

In order to more accurately measure the $(E^0 - E^1)$ term, the change in energy usage as a result of the EEM purchase, regression analysis is performed using the variables related to the categories described above. Observed energy usage is defined as a function of temperature, energy prices, and consumer wages. When analyzing energy usage, Cooling Degree Days (CDDs) and Heating Degree Days (HDDs) are measurements designed to capture the demand for energy usage in response to outside temperatures. CDDs and HDDs convert the daily temperature into measurements which more accurately reflect energy usage. The average daily temperature is compared to the base temperature of 65 degrees. If the average outside temperature exceeds 65 degrees,

[29] Autoregressive and moving average terms account for statistical anomilies related to time that may be in the data. Autocorrelation relates to a link between time and the disturbance term in the estimation equation.

then the difference between the outside and base temperature, is the CDD measurement and the HDD measure takes a value of zero. If the average outside temperature is below 65 degrees, then the difference between base temperature and the outside temperature is the HDD measurements and the CDD measurement takes a value of zero. This is commonly referred to as weather normalization.

To this end, daily maximum and minimum temperatures for the observation period were gathered. Historical daily temperatures were found to be maintained for six locations within the state. Those areas were:

- North Platte
- Norfolk
- North Platte
- Lincoln
- Grand Island
- Omaha

For each location, the daily maximum and minimum temperatures were averaged. The average daily temperature was then compared to the base temperature of 65 degrees to develop CDD and HDD measure for each day during the observation period. Each county within Nebraska was then assigned to the closest of the six weather observation locations.

Chapter V - Estimating the Change in Energy Usage

Many of the projects did not include a precise measure of when the DSM investments were completed. As discussed earlier, the loan information did not contain a date for when the project improvement was completed. Also, on many of the weatherization projects, the only date provided was the date of the final inspection, which could have occurred weeks after a given project was completed. Further, completion dates did not always conform to the billing cycles of energy providers. Thus, the effective date of the implementation of the energy efficiency measures was estimated based upon analysis of changes in the patterns of energy usage of each given consumer.

In order to estimate the period in which the EEM investment occurred, the 36 month energy use panel data was separated in to pre-improvement and post-improvement usage through the employment of an indicator variable. EEMs will generally impact energy usage on Cooling and Heating Degree days as well as general usage. It was assumed the EEMs purchase will not impact energy usage which is a function of energy prices, consumer income, the trend, or any ARMA variables. As such the indicator variable was applied to the constant, HDD, and CDD terms. In discussions with NEO personnel it was determined that while electric energy is used for both cooling and heating purposes, natural gas energy is typically only used for heating purpose. Finally, an energy price series could not be identified for natural gas prices in Nebraska. Thus the following specifications were used:

$$Electric\ Usage = \beta_0^{EL} + \beta_1^{EL} * IND + \beta_2^{EL} * HDD + \beta_3^{EL} * HDD * IND + \beta_4^{EL} * CDD + \beta_5^{EL} * CDD * IND + \beta_6^{EL} * Prices + \beta_7^{EL} * Wages$$

$$Natural\ Gas\ Usage = \beta_0^{NG} + \beta_1^{NG} * IND + \beta_2^{NG} * HDD + \beta_3^{NG} * HDD * IND + \beta_7^{NG} * Wages$$

The CDD and HDD values provide baseline measures of how much cooling and heating is typically required for a given day. The energy usage necessary to fulfill the baseline requirements for cooling and heating should decline after EEM investments are made in equipment such as air conditioning, furnace, and heat pumps. The constant term should account for changes in energy usage not directly related to outside temperature, such as EEM investments in lighting and hot water heaters.

An indicator variable was used to separate the period prior to the EEMs purchase from the following period. The indicator variable took on a value of zero for the periods prior to the EEMs installation and a value of 1 after the installation. In order to estimate the period in which energy usage changed as a result of the EEM purchase, for each included property, the equation specified above were regressed twelve times. In the first regression, the indicator series took on a value of one from the 13th month to the 36th month and zero otherwise. In the second regression, the indicator series took on a value of one from the 14th month to the 36th month and zero otherwise. This process continued to the twelfth pass, where the indicator series took on a value of one from the 24th month to the 36th month and zero otherwise. The regression with the best Akaike Information Criterion (AIC) value was then chosen and the first period in which the indicator series took on a value of one was used as the estimate as to the month during which the change in energy usage associated with the EEMs occurred.

This resulted in electric usage being defined as

$$\textbf{\textit{Prior to EEM installation}}$$

$$Est(Electric\ Usage) = \quad \beta_0^{EL} + \beta_2^{EL} * HDD + \beta_4^{EL} * CDD + \beta_6^{EL} * Prices + \beta_7^{EL} * Wages$$

$$\textbf{\textit{After EEM Installtion}}$$

$$Est(Electric\ Usage) = \begin{array}{l} \beta_0^{EL} + \beta_1^{EL} * IND + \beta_2^{EL} * HDD + \beta_3^{EL} * HDD * IND + \beta_4^{EL} * CDD + \\ \beta_5^{EL} * CDD * IND + \beta_6^{EL} * Prices + \beta_7^{EL} * Wages \end{array}$$

In this analysis, the observed change in energy usage, E0 – E^1, is being sought. So let

$$E^0 = Est(Electric\ Usage)\ Prior\ to\ EEM\ Installation$$
$$E^1 = Est(Electric\ Usage)\ After\ EEM\ Installation$$

Then given that IND takes a value of zero in E^0 and a value of one in E^1, the estimate of electric usage reduces to:

$$E^0 - E^1 = \begin{bmatrix} (\beta_0^{EL} + \beta_2^{EL} * HDD + \beta_4^{EL} * CDD + \beta_6^{EL} * Prices + \beta_7^{EL} * Wages) \\ - \\ \begin{pmatrix} \beta_0^{EL} + \beta_1^{EL} + \beta_2^{EL} * HDD + \beta_3^{EL} * HDD + \beta_4^{EL} * CDD + \\ \beta_5^{EL} * CDD + \beta_6^{EL} * Prices + \beta_7^{EL} * Wages \end{pmatrix} \end{bmatrix}$$

$$E^0 - E^1 = \beta_1^{EL} + \beta_3^{EL} * HDD + \beta_5^{EL} * CDD$$

Similarly, the observed change in natural gas usage reduces to

$$E^0 - E^1 = \beta_1^{NG} + \beta_3^{NG} * HDD$$

The two HDD terms $\beta_3^{EL}\ and\ \beta_3^{NG}$ measure changes in response to heating degree days for electric and natural gas usage respectively. The term β_5^{EL} measures changes in response to cooling degree days for electric usage. The two constant terms $\beta_1^{EL}\ and\ \beta_1^{NG}$ measure all other changes in response to the EEM installation, i.e. changes not associated with heating and cooling degree days.

As part of this phase of the analysis, the effects of two modifications to the regression equations were tested. First the inclusion of ARMA terms was tested. Two different specifications were used.

1. A modified specification with ARMA terms included based on evaluation of the auto-correlation and partial auto-correlation results. If all indicated ARMA terms were significant and the Akaike Information Criteria (AIC) improved as compared to the base specification, then the modified specification was selected.
2. Modified specifications using an AR(1) term, a MA(1) term, MA(1) MA(2) terms, and AR(1) MA(1) terms were created. The specification with the best Akaike Information Criteria (AIC) was then selected, if such specification had a lower AIC than did the base specification.

Next, the effect of leaving and removing of statistically insignificant variables was tested. In the one specification the energy price, wage rate, and trend variables were left in the regression equation regardless of their level of significance. In the second specification, if any of these variables were not statistically significant, the variable was dropped from the specification.

To this end, these tests were combined into three specifications.

1. In the first specification, only ARMA terms indicated by auto-correlation and partial auto-correlation were included and only significant price, wage, and trend variables were retained in the equations.
2. In the second specification, only ARMA terms indicated by auto-correlation and partial auto-correlation were included and all variables were retained.
3. In the third specification, ARMA terms were included based on AIC results and all variables were retained.

These regressions were performed for each of the 339 electric properties and 187 natural gas properties. Given that this requires in excess of 50,000 regressions to be performed and evaluated, as well to ensure consistent evaluation and processing, the regression analysis was performed and evaluated using Eviews command and batch processing language. This processing is referred to as the "Phase 1" program. These three Phase 1 specifications are discussed in more detail later in the paper.

As a first step, indicator series were created for use in identifying the month during which the EEM purchase occurred. These series were created as discussed earlier. Next, a table was created in which to capture the final regression results from each of the 339 and 187 electric and natural gas properties. The following information was collected on each property.

Table V.1
Regression Coefficients and Statistics

- Property ID
- AIC Value
- B_1 Coefficient
- B_1 t-Statistic Value
- B_1 Z Value
- B_1 Chauvenet
- B_1 Modified Chauvenet Value

- Final Specification
- R-Squared Value
- B_3 Coefficient
- B_3 t-Statistic
- B_3 Z Value
- B_3 Chauvenet Value
- B_3 Modified Chauvenet Value

- Assumption Tests
- Durbin-Watson Value
- B_5 Coefficient
- B_5 t-Statistic
- B_5 Z Value
- B_5 Chauvenet Value
- B_5 Modified Chauvenet Value

The Z, Chauvenet, and Modified Chauvenet values were collected for use in measuring behavioral changes and are discussed in more detail under "Phase 2" of this analysis. Also, as discussed earlier, the B_5 results were only captured for electrical properties as this coefficient was not employed in the regression analysis of natural gas properties.

1. Phase 1 Specification #1

For the first specification, the regression analysis was performed in the following manner. Each equation was run twelve times with each run using a different indicator series relative to the estimation of the month in which the EEM purchase/installation occurred. In the first instance, the equation was regressed with the indicator series which identified a change in y intercept and trend occurring in month 13 of the panel data. This equation represents the change in energy usage associated with the EEM purchase occurring in January 2010, the first month in the selected study period. The twelfth equation was regressed with the indicator series which identified a change in y intercept and trend occurring in month 24 of the panel data, which represents the change in energy usage occurring in December 2010. For the purpose of this paper, these twelve regressions are referred to as the "Change Identification" regressions.

Then within each of the twelve regressions, any insignificant coefficients associated with energy prices, wages, and trend variables were dropped in the following manner. First, the error terms were adjusted if heteroskedastic error terms were indicated to be present. Next, the insignificant coefficient with the smallest t-statistic was identified. If the AIC value improves without the indicated series in the specified equation, then the series was dropped from the equation specification. This process continues until all insignificant variables associated with energy prices, wages, trend series were dropped or the AIC did not improve with the removal of an indicated series.

Next, the estimated ARMA “p” and “q” values are calculated. For each equation, 16 lags relative to the autocorrelation and partial autocorrelation functions were analyzed. Beginning with the first lag, the autocorrelation values was compared to a boundary value[30]. If the autocorrelation value exceeded the bound, then the “p” value was incremented. Once a given autocorrelation value did not exceed the bound, the process terminated. A similar process was performed relative to the partial autocorrelation values. The estimated “p” and “q” values were then stored in a table for later use. In 47 of the 339 electric properties, a p value of greater than zero was indicated. In two properties a p value of 2 was indicated. In 85 of the 339 electric properties, a q value of greater than zero was indicated. In four and two properties, q values of 2 and 3 were indicated, respectively. In 47 of the 188 natural gas properties, a p value of greater than zero was indicated. In eight and seven properties, p values of 2 and 3 were indicated. In 76 of the 188 natural gas properties, a q value of greater than zero was indicated. In eight, three, and four properties, q values of 2, 3, and 4 were indicated. Next, the indicated AR and MA terms were added to the equation specification. If all the ARMA terms were significant and the AIC value improved as compared to the base equation, then the ARMA terms were retained in the equation specification. The following ARMA specifications were identified.

[30] The boundary value was calculated as 1.96*n^(1/2).

- ARMA(0,0)
- ARMA(1,1)
- ARMA(1,2)
- ARMA(1,3)
- ARMA(2,1)

Finally the equation specification for each of the twelve indicator series with the best AIC values was retained. Then from among the twelve Change Identification regressions, the specification with the lowest AIC was selected for each electric and natural gas property.

2. Phase 1 Specification #2

Phase 1 Specification #2 was performed in a similar manner as Specification #1 with the exception that all variables were retained. Under Specification #2, within each of the twelve Change Identification regressions, all the coefficients associated with the energy prices, wages, a trend variables were retained, even those that were indicated to be statistically insignificant. Then, from among the chosen twelve Change Identifications regressions, the specification with the lowest AIC was selected for each electric and natural gas property. Similar to Phase 1 Specification #1, ARMA terms were included as indicated by review of the autocorrelation and partial autocorrelation functions. The following ARMA specifications were used.

- ARMA(0,0)
- ARMA(1,1)
- ARMA(1,2)
- ARMA(1,3)

3. Phase 1 Specification #3

Phase 1 Specification #3 was performed in a similar manner as Specification #2 except with the manner in which ARMA terms were added to the calculation. As was done under Specification #2, all coefficients were retained. Under Specification #3, within each of the twelve Change Identification regressions, five ARMA specifications were added to the base regression. These ARMA specifications were ARMA(0,0), ARMA(1,0), ARMA(0,1), ARMA(0,2), and ARMA(1,1). From these five regressions, the specification with the lowest AIC was chosen. Then from among the twelve Change Identification regressions, the specification with the lowest AIC was selected for each electric and natural gas property.

Table V.2 shows the ARMA specifications used under each Phase 1 specification.

Table V.2
Summary of ARMA Specifications

ARMA Specification	Phase 1 Specification Counts		
	#1	#2	#3
ARMA(0,0)	250	255	3
ARMA(0,1)	-	-	100
ARMA(0,2)	-	-	173
ARMA(1,0)	-	-	6
ARMA(1,1)	69	76	57
ARMA(1,2)	5	5	-
ARMA(1,3)	3	3	-
ARMA(2,1)	12	-	-

4. Other Possible Specifications

While there are undoubtedly many variables or alternative specifications to those selected and analyzed in this analysis, there are three which I will specifically note.

One of those specifications would include the ARMA specification a described under Specification #3 while only retaining the energy price, wage, and trend variables if their respective coefficients were significant as was done under Specification #1.

There are several techniques discussed in the literature regarding the fitting of models with error terms. Brockwell and Davis assert that the fit of a model must be checked and the estimation procedure should be repeated for different values of p and q. They advocate using a biased corrected form of the AIC, Akaike's Information Corrected Criterion or AICc, to measure the goodness of fit when employing such a methodology[31]. The AIC and AICc both impose penalties for the inclusion of additional independent variables. However, the AICc imposes a more extreme penalty for large order models. This is designed to counteract the over-fitting nature of the AIC[32]. The formula for the AICc is shown below.

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \ with\ AIC = \left(-2 * \frac{LogLiklihood}{n}\right) + \left(2 * \frac{k}{n}\right)$$

The penalty imposed by the AICc increases as the number of independent variables, k, increases and this penalty grows exponentially as "k" approaches the sample size. Below is a table which demonstrates the incremental increase in AICc with each additional independent variable. The first column is the number of independent variables. The second column shows the incremental increase in AICc with a sample of

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[31] Peter J. Brockwell and Richard A. Davis, *Time Series: Theory and Methods, Second Edition*, (Springer Science & Business Media 1987, 1991), 238.

[32] Liew Khim Sen and Mahnendran Shitan, *The Performance of AICC as an Order Selection Criterion in ARMA Time Series Models*, (Pertanika Jounral of Science & Technology, 10(1): 25-33 January 2002), 4.

36 observations, which is the size on the panel data used in this analysis. The third column demonstrates the incremental increase in AICc with a sample of 360 observations.

Table V.3
Incremental Impact of Each Additional Parameter on AICc

k	N = 36	N = 360
1	0.11765	0.01117
2	0.24599	0.02244
3	0.38636	0.03380
4	0.54032	0.04526
5	0.70968	0.05682
6	0.89655	0.06847
7	1.10345	0.08022
8	1.33333	0.09207
9	1.58974	0.10403
10	1.87692	0.11609
11	2.20000	0.12825
12	2.56522	0.14051

In an effort to quantify the impact of using the AICc in this analysis, a typical regression was chosen. This particular regression contained nine independent variables in its base specification and the AIC was minimized with the inclusion of an ARMA(1,1) specification. However, the AICc rejects the inclusion any ARMA terms. The AIC and AICc were decomposed into the respective SSE and SST terms. Solely for comparison purposes, the R^2 on the ARMA(1,1) specification was 0.9917 and it was 0.9843 without the ARMA specification. For the AICc to improve with inclusion of the ARMA specification, the R^2 value prior to the inclusion of the ARMA terms would need to be less than 0.4550. Thus the AICc would appear to only allow the inclusion of additional terms if there are significant improvements in the fit of the data. The AICc does not allow for incremental improvements in fit when dealing with smaller sample sizes.

This potential issue is referenced by Sen and Shitan, noting that:

> …the performance of AICc in picking up the true models is expected to decline in the case of smaller sample size[33].

For this reason, this method was not employed in this analysis. Rather, the AIC was used to fit the selected ARMA terms under the Phase 1 specifications.

Finally, additional ARMA specifications could be modelled. In their paper, Sen and Shitan, examine ten ARMA specifications[34]. In addition to the specifications used under Phase 1 Specification #3, the ARMA specifications of ARMA(2,0), ARMA(3,0), ARMA(4,0), ARMA(1,2), ARMA(2,1), and ARMA(2,2) could be used. Again due to time constraints, these additional specifications were not used.

On a final note, the interaction between the different steps could also be examined. For example, insignificant variables were excluded before modeling ARMA terms. Other options are to drop insignificant variables after an ARMA specification has been selected or dropped during the fitting of the individual ARMA specifications. This was not explored.

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[33] Sen and Shitan, *The Performance of AICc*, 7.
[34] Sen and Shitan, *The Performance of AICc*, 4.

The results from these three Phase 1 regression specifications were examined to determine whether the specifications produced similar results. To this end, the predicted month during which the EEM purchase/installation occurred was compared for each property in the regression analyses. These results are shown in Table V.4.

Table V.4
Differences in Estimated Month of EEM Installation

	Specification #1	Specification #2	Specification #3	Unique Value
Electric				
Specification #1				84 (25%)
Specification #2	94 (28%)			51 (15%)
Specification #3	201 (59%)	168 (50%)		158 (47%)
Natural Gas				
Specification #1				49 (26%)
Specification #2	57 (30%)			46 (25%)
Specification #3	105 (56%)	102 (55%)		94 (50%)

Specification #1 was used as the base for these comparisons. Under Specification #2, for 28% of the electric properties and 30% of the natural gas properties, a different month in which the EEM installation occurred was indicated. Under Specification #3, for 59% and 56% of the electric and natural gas properties, a different month was indicated. When Specification #3 was compared to Specification #2, similar results were observed, with 50% of the electric properties and 55% of the natural gas properties having a different installation month indicated.

Next, each specification was compared to the other two specifications to see if the indicated month was a unique value, meaning that the month was not indicated in either of the other two specifications. For the electric properties, unique values were indicated in 25%, 15%, and 47% under specifications #1, #2, and #3, respectively. Similarly, unique values were indicated in 26%, 25%, and 50% of the natural gas properties.

Next, the coefficient estimates from each regression were compared. Again using Specification #1 as the base, Table V.5 shows the number of coefficients that both changed signs or whose values varied by more than 20%.

Table V.5

Coefficient Comparison (Specification #1 as Base)

	Coeff Changed Sign		Coeff Changed > 20%	
	Specification		Specification	
	#2	#3	#2	#3
Electric				
Constant	35 (10%)	70 (21%)	129 (38%)	249 (73%)
CDD	14 (4%)	47 (14%)	95 (28%)	220 (65%)
HDD	23 (7%)	70 (21%)	121 (36%)	248 (73%)
Natural Gas				
Constant	35 (19%)	51 (27%)	109 (58%)	150 (80%)
HDD	13 (7%)	24 (13%)	58 (31%)	108 (58%)

10%, 4%, 7% of the coefficients for electric constant, CDD, HDD variables changed sign from Specification #1 to Specification #2, while 21%, 14%, 21% of the coefficients for electric constant, CDD, and HDD variables changed sign from

Specification #1 to Specification #3. Similar results were observed for the natural gas regressions, with 19% and 7% of the electric coefficient related to the constant and HDD variables changing sign from Specification #1 to Specification #2, while 27% and 13% of these coefficients changed sign from Specification #1 to Specification #3.

A comparison of the magnitude of the changes also indicates significant variances amount the three specifications. Relative to Specification #1 for the electric regressions, 38%, 28%, and 36% of the Specification #2 constant, CDD, and HDD coefficients changed more than 20%, while 73%, 65%, and 73% of the Specification #3 constant, CDD, and HDD coefficients changed more than 20%. Similarly, when compared to the Specification #1 natural gas regressions, 58% and 31% of the Specification #2 constant and HDD coefficients varied by more than 20%, while 80% and 58% of the Specification #3 constant and HDD coefficients varied by more than 20%.

This indicates that the differences in results between the three regressions are not trivial. Each Phase 1 specification will likely produce different results regarding the observed behavioral changes. Next the three Phase 1 regression specification results were evaluated to determine if one specification is superior to the others from a statistical standpoint. For this analysis, two comparisons were made. For the first, each set of regression results were evaluated to determine if there is any evidence that the assumptions of a classical regression model with more than one independent variable were violated. Specifically, the following assumptions were tested:

Table V.6

Linear Regression Assumptions

Assumption	Description	Test
$E(e \mid x_j)\ for\ j = 2 \ldots 5$	Model Misspecification	Ramsey RESET test
$Var(e) = \sigma^2$	Heteroskedasticity	Heteroskedasticity Tests
$Cov(e_i, e_j)\ for\ i \neq j$	Error terms are not correlated / Auto-Correlation	Q Statistic Correlogram
		Akaike Information Criteria (AIC)
$x_i = f(x_j)\ for\ i \neq j$	Severe Multi-collinearity	$Auxillary\ R^{2'}s < Model\ R^2$

Heteroskedasticity was identified in between 37% and 62% of the regressions. Accordingly the error terms were adjusted using White's heteroskedasticity consistent covariance matrix estimator.

Similarly, any observed auto-correlation in the error terms can be accounted for by the inclusion of AR terms. AR terms were added based on analysis of Q Statistic Correlogram and analysis of the Akaike Information Criteria (AIC). This is discussed in earlier later in the paper.

Table V.7

Result of Regression Assumptions Tests

	Specification		
	#1	#2	#3s
Electric			
Mis-Specification	220 (65%)	220 (65%)	323 (95%)
Heteroskedasticity	153 (45%)	151 (45%)	141 (42%)
Multi-Collinearity (R2)	162 (48%)	267 (79%)	222 (65%)
Natural Gas			
Mis-Specification	172 (92%)	169 (90%)	181 (97%)
Heteroskedasticity	69 (37%)	66 (35%)	116 (62%)
Multi-Collinearity (R2)	6 (3%)	10 (5%)	6 (3%)

Possible misspecification is shown in 65% of the electrical property regressions using specifications #1 and #2, and in 95% of the electrical properties regressions using specification #3. Possible misspecification is shown in 92%, 90%, and 97% of the natural gas properties regressions using specifications #1, #2, and #3 respectively.

Possible multi-collinearity was observed in 48%, 79%, and 65% of the electrical properties regressions using specification #1, #2, and #3 respectively. While possible multi-collinearity observed in only 6%, 10%, and 6% of the natural gas properties regressions using specification #1, #2, and #3 respectively.

While Specification #1 shows the fewest number of potential violations of the classical regression assumptions, violations are still shown in nearly two thirds of the regressions. With such results, it is difficult to argue that Specification #1 is superior to Specifications #2 and #3.

Next, the AIC and AICc values associated with each regression were examined. The AIC is the best in 86% of the Specification #3 regression equations associated with the electric properties and 82% of the Specification #3 regression equations associated with the natural gas properties. As discussed earlier, the AICc imposes a higher penalty when additional independent variables are added given the small sample size. Thus, when the AICc is used in place of the AIC, Specification #1 best fits the data for the majority of properties in this analysis. The AICc is the best in 91% of the Specification #1 regression equations associated with the electric properties and in 76% of the regression equations associated with the natural gas properties.

Table V.8
Best AIC and AICc Values by Specification

	Specification #1	Specification #2	Specification #3
Electric			
AIC	39 (12%)	9 (3%)	291 (86%)
AICc	309 (91%)	5 (1%)	25 (7%)
Natural Gas			
AIC	24 (13%)	10 (5%)	153 (82%)
AICc	142 (76%)	5 (3%)	40 (21%)

Given the ambiguity of these results, the results from all three specifications were carried forward into Phase 2 of the analysis. For each of the three specifications, the results for the five terms, B_1^{EL}, B_3^{EL}, B_5^{EL}, B_1^{NG}, and B_3^{NG} were combined into individual data sets. This resulted in a total of three data sets for each coefficient or a total of 15 data sets. The electric data sets encompass the electric Phase 1 results for all three specifications and include 339 observations. The natural gas data sets encompass the Phase 1 results for all three specifications and include 187 observations.

5. Phase 1 Results

Table V.9 below summarizes the results for the five indicator variables from the Phase 1 analysis relative to each of the three specifications. Again, these variables indicate the change in either the constant or base energy usage or usage per CDD or HDD resulting from the purchase and installation of an EEM.

Table V.9

Results from Phase 1 Analysis

	Total Projects	Projects with Negative Coefficients		Projects with Positive Coefficients	
	Count	Count	Average	Count	Average
Electric					
Constant, Specification #1	339	171	-443.81	168	335.41
Constant, Specification #2	339	158	-508.24	181	356.72
Constant, Specification #3	339	149	-527.78	190	340.26
CDD, Specification #1	339	179	-1.07	160	0.91
CDD, Specification #2	339	179	-1.10	160	0.88
CDD, Specification #3	339	172	-1.21	167	1.05
HDD, Specification #1	339	163	-0.29	176	0.40
HDD, Specification #2	339	160	-0.28	179	0.42
HDD, Specification #3	339	171	-0.33	168	0.46
Natural Gas					
Constant, Specification #1	187	92	-12.09	95	14.37
Constant, Specification #2	187	83	-16.19	104	18.71
Constant, Specification #3	187	95	-14.80	92	17.23
HDD, Specification #1	187	141	-0.03	46	0.02
HDD, Specification #2	187	144	-0.03	43	0.02
HDD, Specification #3	187	139	-0.03	48	0.02

Using Specification #3 for illustrative purposes, in terms of the changes in electric usage which is not a function of outdoor temperature, i.e. the constant terms, 44% (149) of the projects indicated a reduction in electric usage and 56% (190) were observed to have an increase in electric usage. The changes in electric usage associated with outdoor temperatures were fairly evenly split between observed decreases and increases in electric usage. Relative to natural gas usage, the usage changes associated with non-weather sensitive component were even distributed between observed decreases and increase in usage. However, for heating degree days, nearly 75% (139) of the observations were for decreases in natural gas usage.

Using a 90% confidence interval, Table V.10 shows the percentage of the five indicator variables which are estimated to be statistically difference from zero.

Table V.10

Phase 1 Analysis Coefficients Significant at the 90th Percentile

	Negative Coefficients			Positive Coefficients		
	Specification			Specification		
	1	2	3	1	2	3
Electric Usage						
Constant	55%	52%	54%	49%	47%	54%
CDD	45%	47%	55%	33%	32%	35%
HDD	35%	33%	44%	38%	37%	45%
Natural Gas Usage						
Constant	43%	43%	62%	41%	47%	62%
HDD	65%	62%	71%	43%	42%	58%

In nearly every case, Specification #3 resulted in a higher proportion of statistically significant coefficients relative to the five change indicator variables. The one exception was the electric constant coefficient, B_1^{EL}, with a negative sign. In this case, the proportion of significant variables relative to Specification #3, while higher than Specification #2, was 1 percentage point less than that for Specification #1.

6. Outlier Identification

As part of the behavioral analysis, the coefficient results from Phase 1 were analyzed in an effort to determine if a subset of EEM properties exhibited a different behavioral effect in response to the purchase of EEMs. To this end, a modified version of the Chauvenet Criteria was used to identify those observations for which a more extreme response to the EEM purchase may have occurred. Chauvenet's criterion is a statistical method to identify outliers within a group of data. This method calculates a probability range based on the sample size and the assumption of a normal distribution. The formula for this range is shown below, as are the ranges for the electric and natural gas observation.

General Formula	***Electric Range***	***Natural Gas Range***
$1-\frac{0.5}{n}$	$1-\frac{0.5}{339}=0.998525$	$1-\frac{0.5}{187}=0.997326$

In the case of the electric property, an observation which exceeds this range is assumed to occur in less than 0.15% of observations under a normal distribution. For the use in this analysis, these probability ranges are turned into Z values under the assumption a normal distribution. The critical Z values are shown below.

Electric			***Natural Gas***	
Probability	***Z Value***		***Probability***	***Z Value***
0.998525	2.972916	*and*	0.997326	2.785314

Observations whose Z values exceed the critical values are deemed as outliers and removed from future outlier calculations. Z values for each observation are calculated a shown below.

$$Z_i = (x_i - \bar{x}) \Big/ \left(\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{(n-1)} \right)^{1/2}$$

After the removal of any identified "outlier" observations, the sample size is adjusted to reflect the removal any outliers from the calculations and the analysis is performed again. This iterative process continues until no additional outliers are identified[35].

The analysis contained herein does not drop any observations as a result of the employment of the Chauvenet outlier analysis methodology. Rather, any identified outliers were assigned an indicator value such that the identified observation can be tested to determine if they exhibit a more extreme behavioral response to the purchase of EEMs.

This analysis employed a modified version of the Chauvenet criteria. As the combined data sets were reviewed, clusters of observations were observed towards the tails under a normal distribution curve. In an attempt to account for potential clustering, upper and lower limit Z values associated with a 50% change in the probability of a given observation were created. Next, the number of observations whose Z values fell with this range was counted and the probability of a given observation was increased by the number of observations within this range. For example if the Z values for two observations were within this range, the probability of the observation was doubled. This

[35] See Cleaning Data the Chauvenet Way, Lin, Lily and Sherman, Paul D., SEGUG Proceedings, Paper SA11, Institute of Advanced Analytics.

revised probability was converted into a revised Z value which was then compared to the Critical Chauvenet criterion to determine if the observation was categorized as an outlier.

Chapter VI - Estimating the Amount of EEMs Purchased

Phase 2 of the analysis essentially breaks the Phase 1 regression results into two parts. The first part attempts to model the five coefficients retained from the Phase 1 results as functions of the types and amounts of EEMs purchased. This equates to the $(F^0 - F^1)$ term discussed earlier. The second part of the equation seeks to identify the observed behavioral changes in response to the purchase and installation of EEM. This equates to the (1-b) term discussed earlier.

In order to measures changes resulting from the purchase of EEMs, the relevant coefficients each of the fifteen Phase 1 data sets were regressed against the dollars invested in the seven categories of EEMs[36]. These categories are Air Conditioning, Doors & Windows, Furnace, Heat Pump, Hot Water Heater, Insulation, and Lighting. Similar to Phase 1, Phase 2 was performed using Eviews command and batch processing language due to the number of regressions and to ensure consistent evaluation of results.

In order to attempt to quantify the observed behavioral changes, a series of constant terms were employed. The coefficients on the EEM investment series are

[36] Data was collected on three additional categories of EEMs, Other HVAC, Other Appliances, and Miscellaneous. Due to concerns about the accuracy and the number of observations for these three categories, the data was not used in this analysis. Much of the data appeared to be related to health and safety concerns rather than energy usage. This it would appear this exclusion should have a minimal impact on energy usage.

designed to pick up changes in energy usage associated with EEM purchases based on the amount invested. The coefficients on the constant terms are designed to pick up all other changes in energy usage. For the purposes of this analysis, the constant terms pick up the behavioral changes. Two types of constants are used in the Phase 2 analyses. The first are generally applicable constant terms which apply to the entire population and/or the NEO Weatherization or Loan program sub populations. The second apply to the subsets identified in the outlier analysis discussed above and are referred to as subset constants. These subset constant terms are split into four categories:

- Negative Coefficients in Weatherization Program
- Negative Coefficients in Loan Program
- Positive Coefficients in Weatherization Program
- Positive Coefficients in Loan Program

Below is the general regression form of the Phase 2 analysis.

$$Usage = F\begin{pmatrix} EEM\ Investment_1 \\ EEM\ Investment_2 \\ \vdots \\ EEM\ Investment_i \end{pmatrix} + G\begin{pmatrix} General\ Constant_1 \\ General\ Constant_2 \\ \vdots \\ General\ Constant_j \end{pmatrix} + H\begin{pmatrix} Subset\ Constant_1 \\ Subset\ Constant_2 \\ \vdots \\ Subset\ Constant_k \end{pmatrix}$$

To facilitate this analysis, a number of additional series were created. First, indicator series were created to reflect whether the EEM purchase(s) occurred under the NEO's loan or weatherization programs.

Next, "Behavioral" indicator series were created to reflect the potential outliers identified through the Modified Chauvenet Criteria discussed earlier. This outlier test was employed in two ways. First, only observations which were identified in the first pass were identified as potential outliers. Second, all observations identified as outliers were flagged. Further, each of the two series was further disaggregated into observations with negative and positive values. This resulted in the creation of four indicator series.

Indicator series were created to identify those observations whose Z values exceeding 5 standard deviations and were also disaggregated into observations with negative and positive observations.

Also created was a series to reflect Heat Pump EEM purchases for those properties for which the heat pump purchases appeared to replace an existing heat pump. These properties were identified through analysis of electric usage data. Properties that exhibited historical spikes in electric usage in response to both Cooling Degree Days and Heating Degrees Days were identified as likely have an existing heat pump by this indicator series.

Finally, a natural log series was created for each of the seven EEM purchase series. This was done programmatically to accommodate for zero values in the EEM investment series. The EViews log function returns an error term when applied to zero value. In these seven log series, EEM investment amounts with a zero value are programmatically assigned a zero value. All other observations are assigned an amount equal to the natural log of the EEM purchase amount.

The following base specifications were used for each of the five coefficients.

$$
\begin{aligned}
Elec\ Constant\left(\beta_1{}^{EL}\right) &= \quad F(AC\$, DW\$, Furn\$, Insl\$, Lite\$) \\
Elec\ HDD\left(\beta_3{}^{EL}\right) &= \quad F(DW\$, Furn\$, Insl\$\ HP\$, CurrHP\$\ ) \\
Elec\ CDD\left(\beta_5{}^{EL}\right) &= \quad F(AC\$, DW\$, Furn\$, Insl\$, HP\$, CurrHP\$) \\
NG\ Constant\left(\beta_1{}^{NG}\right) &= \quad F(DW\$, Furn\$, Insl\$, Hwh\$) \\
NG\ HDD\left(\beta_3{}^{NG}\right) &= \quad F(DW\$, Furn\$, HP\$, Hwh\$, Insl\$)
\end{aligned}
$$

Not all investment series were used in the base specification for the five energy change coefficients. In order to reduce the likelihood of spurious results, EEM investment series were not included in Phase 2 regression where a causal relationship did not seem likely, e.g. Natural Gas usage in response to heating degree days as a function of EEM investments in air conditioning. This resulted in the EEM investments series being used twenty five times in the Phase 2 regressions. These five Phase 2 Investment specifications were used with the applicable Phase 1 data sets.

Next, five potential general behavioral changes were tested on each investment specification through the use of generally applicable constant terms. First, the base investment specification was used and no behavioral response was tested. This was accomplished by including no general constant terms. Second, the investment specification was modified to assume a similar behavioral response in both the Loan and Weatherization programs participants. This was done by the inclusion of a normal constant term. Third, the base specification was modified to assume only a behavioral response from participants in the weatherization program. This was accomplished by the inclusion of the Weatherization Program indicator series. Fourth, the base specification was modified to assume only a behavioral response from participants in the Loan program. Similarly, this was done through the inclusion of the Loan Program indicator series. Fifth, the base specification was modified to assume distinct behavioral responses from both the weatherization and loan programs. This was accomplished with the inclusion of both the Weatherization and Loan program indicator series. These modifications are shown to the base investment specification for the electric constant term, β_1^{EL}, is shown below.

$$\beta_1{}^{EL} = \alpha_1 AC\$ + \alpha_2 DW\$ + \alpha_3 Furn\$ + \alpha_4 Insl\$ + \alpha_5 Lite\$$$

$$\beta_1{}^{EL} = \alpha_{0,Gen} + \alpha_1 AC\$ + \alpha_2 DW\$ + \alpha_3 Furn\$ + \alpha_4 Insl\$ + \alpha_5 Lite\$$$

$$\beta_1{}^{EL} = \alpha_{0,Gen,Wx} WX_{IND} + \alpha_1 AC\$ + \alpha_2 DW\$ + \alpha_3 Furn\$ + \alpha_4 Insl\$ + \alpha_5 Lite\$$$

$$\beta_1{}^{EL} = \alpha_{0,Gen,Ln} Loan_{IND} + \alpha_1 AC\$ + \alpha_2 DW\$ + \alpha_3 Furn\$ + \alpha_4 Insl\$ + \alpha_5 Lite\$$$

$$\beta_1{}^{EL} = \begin{pmatrix} \alpha_{0,Gen,Wx} WX_{IND} \\ + \\ \alpha_{0,Gen,Ln} Loan_{IND} \end{pmatrix} + \alpha_1 AC\$ + \alpha_2 DW\$ + \alpha_3 Furn\$ + \alpha_4 Insl\$ + \alpha_5 Lite\$$$

Next each specification was augmented under four different methods of identifying any observed behavioral response within the subsets identified in the outlier test described earlier. Under the first method, a uniform behavioral response across all observations is tested through the use of only the general constant terms. Under the second method, in addition to the general constant terms, the premise that a subset of observations exhibits a more extreme behavioral response is tested. This was done through the use of the behavioral subset indicator series which were discussed earlier. Under this method, the indicator series which reflects all the identified observations was used. The third method employs the same process as the second method with the exception that observations which exceed 5 standard deviations were excluded from the regression analysis. The fourth method using the same process as the third method, except rather than all identified outliers, only those outliers identified in the first pass of the modified Chauvenet criteria are used.

Each of these modified base specifications were revised to include the specified subset indicator series as discussed earlier. Below is an example of this applied to the electric constant specification with the assumption of distinct generally applicable behavior responses in the Weatherization and Loan programs.

$$\beta_1{}^{EL} = \begin{array}{l} \alpha_1 AC\$ + \alpha_2 DW\$ + \alpha_3 Furn\$ + \alpha_4 Insl\$ + \alpha_5 Lite\$ + \alpha_6 WX_{IND} + \alpha_7 Loan_{IND} + \\ \alpha_{0,Neg,Wx}(ModChauv\_Neg_{IND} * WX_{IND}) + \alpha_{0,Neg,Ln}(ModChauv\_Neg_{IND} * Loan_{IND}) + \\ \alpha_{0,Pos,Wx}(ModChauv\_Pos_{IND} * WX_{IND}) + \alpha_{0,Pos,Ln}(ModChauv\_Pos_{IND} * Loan_{IND}) \end{array}$$

Each specification was tested for Heteroskedasticity and if such was indicated, the error terms were adjusted accordingly. Then each specification was run through a fitting algorithm.

Two passes were performed under the fitting algorithm. First, the coefficients for all EEM investment series in the base investment specification were retained. In the second, investment series whose coefficients were positive were dropped based on the assumption that coefficient results should be negative[37]. There were two exceptions to this assumption. The first exception was to the Heat Pump series in the Electric HDD

[37] The test was performed on the base specification only. If the initial sign on a coefficient was negative, the investment series was dropped. In some cases, as an artifice of the fitting process, the sign of the coefficient on an investment series, while initially negative, became positive. In these instances, if significant, the investment series was retained.

series. This coefficient measures the change in energy usage in response to the installation of a new heat pump. A new heat pump potentially shifts energy usage from natural gas to electric. While, in total, the assumption is a reduction in overall energy usage, an increase in electric usage as a function of heating degree days was generally observed when a new heat pump was installed. In terms of total energy costs, the increase in electric usage is offset by a reduction in natural gas usage. The second exception was to hot water heater investments in the Natural Gas Constant series. An increase in natural gas usage was generally observed in this series in response to hot water heater investment. The assumption is that in response to either a larger capacity unit and/or a more efficient unit being installed, customers increased energy usage by using more hot water.

Finally, the relationships between the EEM investment series and the changes in energy usage were tested. The regression analyses underlying this paper are dependent on the relationships between the dependent variable and independent variables being linear in nature. To test this assumption, each investment series was subjected to three transformations to determine if such transformations improved the fit of the data as measured by the relevant t-statistic and AIC. The three transformations employed in this test were:

- Taking the square root of each investment series (Inv$^0.5),
- Taking the natural log of each investment series (Log(Inv$)), and
- Raising each investment series to the 0.01 power (Inv$^0.01).

In recognition that transforming one independent variable may impact the coefficients associated with the other independent variables, the investment variables were transformed based on the base t-statistic values beginning with the smallest value, i.e. the least significant. Further, again in recognition of interrelationship between the independent variables, after each series was fitted under the transformation portion of the fitting algorithm, each variable was restored to initial specification to ensure that transformed specification still resulted in the lower t-statistic and AIC in light of the transformations made to the other independent variables. Finally, any investments variables which were still shown as not significant at the 90^{th} percentile were dropped from the equation.

This analysis produced 1,200 separate regression results for consideration. This represents 240 equations for each of the five Beta coefficients or 80 for each of the Phase 1 datasets. These regressions are shown generally below:

- Five Coefficients from Phase 1 Specification Regressions
    - Electric Constant (β_1^{EL})
    - Electric Heating Degree Days (β_3^{EL})
    - Electric Cooling Degree Days (β_5^{EL})
    - Natural Gas Constant (β_1^{NG})
    - Natural Gas Heating Degree Days (β_3^{NG})
- Three Phase 1 Specifications
    - Indicated ARMA & Only Significant Variables Retained
    - Indicated ARMA & All Variables Retained
    - ARMA Fitted with AIC & All Variables Retained
- Five Generally Observed Behavioral Changes

  - None Observed
  - Same Change in Both Weatherization and Loan Programs (C)
  - Only Observed in Weatherization Program (IND_Wx)
  - Only Observed in Loan Program (IND_Loan)
  - Different Observed Change in Weatherization and Loan Programs (IND_Wx & IND_Loan)
- Four Subset/Outlier Observed Behavioral Changes
  - None Observed
  - Change Observed in All Identified Outliers
  - Change Observed in All Identified Outliers excluding Observations greater than 5 Standard Deviations from the Mean
  - Change Observed in Outliers Identified in the First Pass with the Modified Chauvenet Criteria excluding Observations greater than 5 Standard Deviations from the Mean
- Two Investment Specifications
  - All Variables Retained
  - Only Variables with Negative Coefficients Retained
- Fitted Specifications
  - Base/Linear Specification
  - Transformed Specification

Appendix A contains a map of the Phase 2 regression processes.

The next step was to pick a specification from which to estimate the behavioral changes associated with the EEM investments under the NEO's Weatherization and Loan programs. The primary tool to select between the specifications was the AIC. Given the nature of the transformation algorithm employed in this analysis, the Transformed specification produced AIC results either equal or superior to the Base/Linear Specification. Therefore the Transformed Specification was used.

Among the subset behavioral changes, the third specification produced the best AIC values. This specification excluded observations greater than 5 standard deviations from the mean and treated all remaining identified outliers as a subset with additional behavioral changes. The second specification, which included all observations and similarly treated all outliers as a subset with additional behavior changes, produced the second best AIC values. These results indicate two things. First, the differences from the mean for the identified outlier observations are not the results of a greater or lesser purchase of EEMs, as that result would be shown in the investment coefficients rather than the subset behavioral coefficients. Second it shows that those observations that are greater than 5 standard deviations from the mean show a different response than the other identified outliers. These extreme results could be a case of broken or extremely inefficient existing electrical and/or natural gas infrastructure in the given property. However, the survey screened for these types of properties and, when identified, such properties were removed from the sample. Thus a good rationale to exclude such variables could not be found and the results from the second subset behavioral specification were used.

Next, the AIC values were reviewed from the fitted, second subset specifications. The specification with the lowest AIC values was selected. In this manner the generally observation behavior specification was selected from among the five possible specifications.

Combined 25 investment variables were regressed across the 5 coefficient identified in Phase 1 of this analysis. When all significant variables, as well as coefficients with both positive and negative signs, are retained, under Specification #1, 14 of the coefficients, in 6 of 7 investment categories were significant. Under Specification #2, 17 coefficients, in 6 of 7 investment categories were significant, and under Specification #3, 17 coefficients in all 7 investment categories were significant. When only significant, negative coefficients were retained, under Specification #1, 12 coefficients in 5 of the 7 investment categories were retained. Under Specification #2, 11 coefficients in 6 of the 7 investment categories were retained. Under Specification #3, 16 coefficients in all 7 investment categories were retained. Under the Phase 1 analysis, Specification #3 was shown to include more statistically significant change variables. Given the more robust results, Phase 1 Specification #3 was chosen.

The specification in which only the negative coefficients were retained was chosen. For the electrical terms, both this specification and the specification retaining all variables produce identical results. For the natural gas constant term, the "All" specification retains a coefficient for the investment series INSL$$^{0.01}$. Unless there is an inherent flaw in the EEM program or the installation of the EEM, the installation of an EEM, in and of itself, will not increase energy usage. Increases in energy usage for purposes of this analysis are considered behavioral changes. The primary difference between the investment variables and the behavioral variables is that while the behavioral variables are expect to have a constant effect, while the investment variables are expected to vary with the amount of a given expenditure. In the case of a positive coefficient on an investment variable, a case could be made that this is also represents a change in behavior. Rather than a constant change, a behavioral change is being observed based on the amount invested, in this case, in insulation. If true, given the positive coefficient on the investment term, it would appear that the expectation of energy saving is greater than that which is actually realized through the EEM purchase. Moreover, the identified transformation on insulation investment is raised to the 0.01 which more closely approximates a constant effect than does either of the other tested transformation or a linear specification.

Finally, on Natural Gas Heating Degree Days (HDD), there are some more pronounced differences. Both specifications include heat pumps, hot water heaters, and insulation. However, the transformations on the heat pump and insulation investment series are different between the two specifications. The All specification includes a positive coefficient on doors & windows investment while the Negative specification includes negative coefficient on furnace investment. Further the All specification shows a general but different observed behavioral change for the Weatherization and the Loan Programs while the Negative Specification shows no generally applicable behavioral changes. The AIC is better on the “All” specification. Similar to the natural gas constant regression, the selected transformation on doors & windows raises the investment series to the 0.01 power. Thus this result may again be more reflected of a behavioral change than a result of the EEM installation. If this is indeed true, then perhaps the coefficient on furnace investments under the negative specification is less significant than the behavior changes under the all specification. However, given that a disaggregation of positive coefficients on investment terms into behavior and EEMs was not undertaken, for consistency purposes, the negative specification was used.

Appendices B-1 through B-5 contain examples of the base and fitted specifications as well as the selection of general observed behavioral specification[38]. Appendices C-1 and C-2 contain comparisons between the three Phase 1 specifications for the negative only investment coefficients and all investment coefficients regressions. Appendix D contains a comparison between the negative only investment coefficients and all investment coefficients regressions.

Chapter VII - Deriving the Estimated Behavioral Change

First the coefficients for the generally observed and subset behavioral changes were aggregated to develop an estimate of the expected coefficient which could then be applied uniformly across the entire project sample included in this analysis. The general constant coefficient, if indicated, was assumed to apply to the entire population. The subset behavioral coefficients, if indicated, are assumed to apply to only a subset of the general population. This subset was expressed as a percentage of number of observations in a given subset compared to the total number of observations. The formula for expected behavioral change is shown below. For each of the five coefficients from the Phase 1 regressions, the estimated behavioral coefficients were combined in the manner shown below. The four subset behavioral coefficients are weighted by the number of observation in their respective subsets relative to the total number of observations in the weatherization and loan programs.

[38] This example contains the results for the five Phase 1 coefficients from Phase 1 Specification #4 and includes all identified outliers and all observations.

$$\alpha_{0,Wx} = \left[\begin{array}{ccc} \alpha_{0,Gen} & + & \alpha_{0,Gen,Wx} \quad + \\ \left(\alpha_{0,Neg,Wx} * \frac{Obs_{Neg\_Wx}}{Obs_{Total,Wx}}\right) & + & \left(\alpha_{0,Pos,Wx} * \frac{Obs_{Pos\_Wx}}{Obs_{Total,Wx}}\right) \end{array} \right]$$

$$\alpha_{0,Ln} = \left[\begin{array}{ccc} \alpha_{0,Gen} & + & \alpha_{0,Gen,Wx} \quad + \\ \left(\alpha_{0,Neg,Ln} * \frac{Obs_{Neg\_Ln}}{Obs_{Total,Ln}}\right) & + & \left(\alpha_{0,Pos,Ln} * \frac{Obs_{Pos\_Ln}}{Obs_{Total,Ln}}\right) \end{array} \right]$$

This resulted in the creation of 10 estimated behavioral coefficients as shown below.

Table VII.1
Combined Estimated Behavioral Coefficients

Phase 1 Series	Weatherization		Loan	
Elec Constant (β_1^{EL})	$\alpha_{0,Wx,\beta(1,EL)}$	223.10705	$\alpha_{0,Ln,\beta(1,EL)}$	(35.12347)
Elec HDD (β_3^{EL})	$\alpha_{0,Wx,\beta(3,EL)}$	0.23293	$\alpha_{0,Ln,\beta(3,EL)}$	0.06416
Elec CDD (β_5^{EL})	$\alpha_{0,Wx,\beta(5,EL)}$	0.50736	$\alpha_{0,Ln,\beta(5,EL)}$	0.29028
NG Constant (β_1^{NG})	$\alpha_{0,Wx,\beta(1,NG)}$	0.98737	$\alpha_{0,Ln,\beta(1,NG)}$	1.70954
NG HDD (β_3^{NG})	$\alpha_{0,Wx,\beta(3,NG)}$	(0.00035)	$\alpha_{0,Ln,\beta(3,NG)}$	(0.00250)

Estimated behavioral coefficients with positive signs indicate increased energy usage, while negative indicate decreased usage. Increased energy usage in response to the purchase of EEM would be expected given the assumption that comfort is an ordinary good. Seven of the ten behavioral coefficients show an increase in usage in response to the purchase of EEMs. The coefficient on the electric constant term, β_1^{EL}, for the Loan program, has a negative sign. Relative to this coefficient, the selected Phase 2 specification for only includes a generally observed constant term for the weatherization program projects. Pursuant to the Phase 2 methodology, this specification resulted in the best AIC value. The negative coefficient is the result of the combination of the negative and positive behavioral subset variables. In this instance the weighted coefficient on the negative observations was larger than the weighted coefficients on the positive observations within the respective sub-sets. The Phase 2 specification containing general constant terms for both the weatherization and loan programs was very close to the selected specification in terms of the AIC value, differing by less than 0.01%. If this specification was used, the combined constant term coefficient would have positive for the loan program similar to the weatherization program coefficient.

The estimated behavioral coefficients on the Natural Gas HDD term, β_3^{NG}, have negative signs for both the weatherization and loan programs. The selected Phase 2 specification for this term includes no generally observed constant terms for either the weatherization or loan program observations. Similar to the electric constant term, the weighted coefficient on the negative observations was larger than the weighted coefficients on the positive observations within the respective sub-sets. In reviewing the four specifications which contained generally observed behavioral constant terms, the signs on these coefficients were all negative.

However, given the potential inter-relationships between the various categories of EEM purchases, examining the behavioral coefficients in isolation may not present an accurate view. As such, the behavior impact, “b”, was measured in the following ways

- Weatherization, Electric
- Weatherization, Natural Gas
- Weatherization, Total
- Loan, Electric
- Loan, Natural Gas
- Loan, Total

The formula from which the behavior impact is derived is shown below.

$$(E_0 - E_1) = (F_1 - F_0) * (1 - b)$$
$$\frac{(E_0 - E_1)}{(F_1 - F_0)} = 1 - b$$
$$b = 1 - \frac{(E_0 - E_1)}{(F_1 - F_0)}$$

The term, $(F_1\text{-}F_0)$, represents the impact of the EEM purchase, which excludes any behavioral changes. For purposes of this analysis, $(F_1\text{-}F_0)$ is equal to the EEM investment portion of the selected Phase 2 regressions. These specifications associated with each regression are shown below.

$$\hat{\beta}_1^{EL}(F_1 - F_0) = \left(\alpha_{1,\beta(1,EL)} * (Insl\$^{0.5}) + \alpha_{2,\beta(1,EL)} * Ln(Lite\$)\right)$$
$$\hat{\beta}_3^{EL}(F_1 - F_0) = \left(\alpha_{1,\beta(3,EL)} * (Insl\$^{0.01}) + \alpha_{2,\beta(3,EL)} * HP\$ + \alpha_{3,\beta(3,EL)} * (CurrHP\$^{0.5})\right)$$
$$\hat{\beta}_5^{EL}(F_1 - F_0) = \begin{pmatrix} \alpha_{1,\beta(5,EL)} * DW\$ + \alpha_{2,\beta(5,EL)} * (Furn\$^{0.01}) + \alpha_{3,\beta(5,EL)} * (Insl\$^{0.01}) + \\ \alpha_{4,\beta(5,EL)} * AC\$ + \alpha_{5,\beta(5,EL)} * (HP\$^{0.01}) \end{pmatrix}$$
$$\hat{\beta}_1^{NG}(F_1 - F_0) = \left(\alpha_{1,\beta(1,NG)} * DW\$ + \alpha_{2,\beta(1,NG)} * HWH\$\right)$$
$$\hat{\beta}_3^{NG}(F_1 - F_0) = \begin{pmatrix} \alpha_{1,\beta(3,NG)} * (Furn\$^{0.5}) + \alpha_{2,\beta(3,NG)} * (HP\$^{0.01}) + \alpha_{3,\beta(3,NG)} * HWH\$ + \\ \alpha_{4,\beta(3,NG)} * Ln(Insl\$) \end{pmatrix}$$

Next, in order to combine the terms, the regression estimates must be equalized. The Constant terms are in billing months, the HDD terms are in heating degree days, and the CDD term is in cooling degree days. In order to accomplish this, the regression estimates were annualized. The annualizing factors are shown in Table VII.2 below. The regression results for the Electric Constant, β_1^{EL}, and the Natural Gas Constant, β_1^{NG}, are in billing months. As such the annualizing factors for these two terms represent the average number of bills per years and were calculated are follows.

$$\begin{array}{rcccl} & 371{,}231 & \textbf{Billing Days in Sample} & 205{,}035 & \\ & 12{,}204 & \textbf{Bills in Sample} & 6{,}732 & \\ 30.41880 = & \frac{371{,}231}{12{,}204} & \textbf{Days per Bill} & \frac{205{,}035}{6{,}732} & = 30.45677 \\ 11.99916 = & \frac{365}{30.41880} & \textbf{Bills Per Year} & \frac{365}{30.45677} & = 11.98420 \end{array}$$

The regressions results for the Electric HDD, β_3^{EL}, and Natural Gas HDD, β_3^{NG}, are in heating degree terms. As such the annualizing factor is the average number of heating degree days per year in Nebraska based upon the data obtained from the six weather observations sites in Nebraska from 2000 through 2010. The annualizing factor for the Electric CDD, β_5^{EL}, was calculated in a similar manner and is reflective of the annual cooling degree days in Nebraska.

Table VII.2

Annualizing Factors

Coefficient	Factor
Electric Constant, $\hat{\beta}_1^{EL}$	11.99916
Electric HDD, $\hat{\beta}_3^{EL}$	6,262.34
Electric CDD, $\hat{\beta}_5^{EL}$	1,051.39
Natural Gas Constant, $\hat{\beta}_1^{NG}$	11.98420
Natural Gas HDD, $\hat{\beta}_1^{EL}$	6,262.34

The annualizing factors are used equalize results within each energy source. Thus, the electric results can now be expressed in terms of annual kilowatt hours, kwh/year, and natural gas results in terms of annual therms, therms/year. Below is the manner in which the Phase 2 regression results were combined.

$F_1 - F_0$ terms represents the estimated impact of the EEM purchases, which excludes any estimated behavioral changes. These estimated impacts, resulting from the identified investment coefficients discussed earlier, are summed across the sample based on the program in which a given property participated. This total is then annualized using the appropriate factor. Then the three electric regression results are added together as are the two natural gas regression results. This provides an estimate of the total change in electric usage and natural gas usage for properties participating in the weatherization program and the loan program. Below is the formulas used to aggregate the electric and natural gas usage for properties participating in the weatherization program. Similar calculations were done for properties which participated in the loan program.

Electric, Weatherization Program

$$(F_1 - F_0)_{EL,Wx} = \begin{bmatrix} 11.99916 * \left(\sum_{i=1}^{339} \hat{\beta}_1^{\ EL} (F_1 - F_0)_i, \ \ If\ Wx_{IND} = 1 \right) \\ + \\ 6{,}262.34 * \left(\sum_{i=1}^{339} \hat{\beta}_3^{\ EL} (F_1 - F_0)_i, \ \ If\ Wx_{IND} = 1 \right) \\ + \\ 1{,}051.39 * \left(\sum_{i=1}^{339} \hat{\beta}_5^{\ EL} (F_1 - F_0)_i, \ \ If\ Wx_{IND} = 1 \right) \end{bmatrix}$$

Natural Gas, Weatherization Program

$$(F_1 - F_0)_{NG,WX} = \left[\begin{array}{c} 11.9842 * \left(\sum_{i=1}^{187} \hat{\beta}_1{}^{NG} (F_1 - F_0)_i\,,\ \ If\ Wx_{IND} = 1\right) \\ + \\ 6{,}262.34 * \left(\sum_{i=1}^{187} \hat{\beta}_3{}^{NG} (F_1 - F_0)_i\,,\ \ If\ Wx_{IND} = 1\right) \end{array}\right]$$

Next the total change in energy usage was estimated. This includes any estimated behavioral changes. This calculation consists of adding the annualized estimated behavior changes to the annual EEM purchase changes, the $F_1 - F_0$ terms, calculated above. The estimated behavioral changes for each projected are aggregated by energy type and NEO program. These totals are then annualized using the appropriate factor. Below is the formulas used to aggregate the electric and natural gas usage for properties participating in the weatherization program. Similar calculations were done for properties which participated in the loan program.

Electric, Weatherization Program

$$(E_0 - E_1)_{EL,Wx} = \quad (F_1 - F_0)_{EL,Wx} + \left[\begin{array}{c} 11.99916 * \left(\sum_{i=1}^{339} \alpha_{0,Wx,\beta(1,EL)},\ \ If\ Wx_{IND} = 1\right) \\ + \\ 6{,}262.34 * \left(\sum_{i=1}^{339} \alpha_{0,Wx,\beta(3,EL)},\ \ If\ Wx_{IND} = 1\right) \\ + \\ 1{,}051.39 * \left(\sum_{i=1}^{339} \alpha_{0,Wx,\beta(3,EL)},\ \ If\ Wx_{IND} = 1\right) \end{array}\right]$$

<u>Natural Gas, Weatherization Program</u>

$$(E_0 - E_1)_{NG,WX} = \quad (F_1 - F_0)_{NG,WX} + \left[\begin{array}{c} 11.9842 * \left(\sum_{i=1}^{187} \alpha_{0,Wx,\beta(1,NG)}, \;\; If\ Wx_{IND} = 1 \right) \\ + \\ 6{,}262.34 * \left(\sum_{i=1}^{187} \alpha_{0,Wx,\beta(3,NG)}, \;\; If\ Wx_{IND}\ 1 \right) \end{array} \right]$$

A summary of the estimated changes in energy usage is shown below.

Table VII.3

Summary of Estimated Changes in Energy Usage

Category	$E_0 - E_1$	$F_1 - F_0$
Electric, Weatherization	(83,566.41)	(821,301.09)
Electric, Loan	(67,783.71)	(113,462,41)
Natural Gas, Weatherization	(6,797.63)	(7,619.42)
Natural Gas, Loan	(10,078.92)	(10,570.48)

The estimated total change in energy usage and the estimated change in energy usage associated with the EEM purchases are then used to estimate the observed behavior changes. The formula for estimating the behavior change is again shown below.

$$b = \quad 1 - \frac{(E_0 - E_1)}{(F_1 - F_0)}$$

Using the estimate changes in energy usage, the following behavioral impacts are estimated.

$$b_{Wx}{}^{EL} = 1 - \frac{(83{,}566.41)}{(821{,}301.09)} = 0.8983$$

$$b_{Ln}{}^{EL} = 1 - \frac{(61{,}783.71)}{(113{,}462.41)} = 0.4555$$

$$b_{Wx}{}^{NG} = 1 - \frac{(6{,}797.63)}{(7{,}619.42)} = 0.1079$$

$$b_{Ln}{}^{NG} = 1 - \frac{(10{,}078.92)}{(10{,}570.48)} = 0.0465$$

Relative to electric usage, the observed behavioral changes is 89.83% for projects participating in the weatherization programs and 45.55% for projects participating in the loan program. Thus, on average, for each kwh of electric energy saved through the purchase of EEMs, a participant in the weatherization program changes their behavior to use an additional .8983 kWh of electricity. Similarly, a participant in the loan program changes their behavior to use an additional 0.4555 kWh of electricity in response to an EEM purchase. The estimated behavioral response observed for participants in the weatherization program is twice as large as that observed in participants in the loan program.

A similar relationship was observed in behavioral response relative to natural gas usage. A participant in the weatherization program responded to the purchase of EEMs by using 0.1079 additional therms for each therm saved. A participant in the loan program changes their behavior to use an additional 0.0465 therms of natural gas in response to an EEM purchase. This is a 2.3 to 1 ratio.

To compare the behavior response between participants in the weatherization and loan program across energy sources, the estimated changes in energy usage need to be equalized in terms of dollars spent. For this purpose, an electric price, P_{EL}, of \$0.08/kwh and a natural gas price, P_{NG}, of \$1.1045/therm was used.

$$(E_0 - E_1)_{Wx} = \left[(E_0 - E_1)_{EL,WX} * P_{EL}\right] + \left[(E_0 - E_1)_{NG,WX} * P_{NG}\right]$$
$$(F_1 - F_0)_{Wx} = \left[(F_1 - F_0)_{EL,WX} * P_{EL}\right] + \left[(F_1 - F_0)_{NG,WX} * P_{NG}\right]$$

A similar calculation was done for projects participating in the loan program. The results of this aggregation are shown below.

$$(E_0 - E_1)_{Wx} = (\$14{,}193.30) = [(83{,}566.41) * \$0.08] + [(6{,}797.63) * \$1.1045]$$
$$(F_1 - F_0)_{Wx} = (\$74{,}119.74) = [(821{,}301.09) * \$0.08] + [(7{,}619.42) * \$1.1045]$$
$$(E_0 - E_1)_{Ln} = (\$16{,}074.87) = [(61{,}783.71) * \$0.08] + [(10{,}078.92) * \$1.1045]$$
$$(F_1 - F_0)_{Ln} = (\$20{,}752.09) = [(113{,}462.41) * \$0.08] + [(10{,}570.48) * \$1.1045]$$

Applying the formula used to estimate behavior changes, gives the following results.

$$b_{Wx} = 1 - \frac{(\$14{,}193.30)}{(\$74{,}119.74)} = 0.8085$$
$$b_{Ln} = 1 - \frac{(\$16{,}074.87)}{(\$20{,}752.09)} = 0.2254$$

When expressed in terms of dollars, a participant in the weatherization program responds to each dollar of energy savings associated with the purchase of EEMs by using \$0.8085 in additional energy. A participant in the loan program uses an additional \$0.2254 in energy in response to each dollar of savings. This is a 3.6 to ratio, nearly double the estimated amount when looking at energy usage. This increased ratio is the result of the relatives of the energy changes between electric and natural gas usage between the weatherization and loan program. In the weatherization program, change in electric usage makes up 89% of the total change in dollars. In the loan program, the change in electric usage accounts for only 44% of the total change in dollars.

Chapter VIII - Estimated Impact of Additional Dollars Invested In EEMs

As discussed earlier, eight EEM investment series were used in the Phase 2 regression analysis. These eight EEM investments series were used as independent data series for the five coefficients identified in the Phase 1 regression. This allowed for a possible total of 40 (8 x 5) EEM Investment coefficients. However, in order to reduce the likelihood of spurious results, the EEM investment series were not included in Phase 2 regression were a causal relationship did not seem likely, e.g. Natural Gas usage in response to heating degree days be a function of EEM investments in air conditioning. This resulted in the EEM investments series being used twenty five times in the Phase 2 regressions.

Based on the selected Phase 2 regressions, the included EEM investment series were found to be significant in sixteen of the twenty five instances. As discussed earlier, in addition to testing for a linear relationship between the EEM investments and the change in energy usage, three transformations were applied to the included EEM investment series in order to test for non-linear relationship. Specifically, the transformations tested were EEM investment series raised to the 0.5 power, EEM investment series raised to the 0.01 power, and the natural log of the EEM investment series. This purpose of these transformations is to test for diminishing marginal returns relative to each additional dollar of EEM investment for a given category. The Table VIII.1 below shows EEM investment series and selected transformations.

Table VIII.1

EEM Investment Series Transformations

EEM Investment		B_1^{EL}	B_3^{EL}	B_5^{EL}	B_1^{NG}	B_3^{NG}
Air Conditioning		InSig		---		
Doors & Windows		InSig	InSig	---	---	InSig
Furnace		InSig	InSig	^0.01	InSig	^0.05
Heat Pump	New		---	^0.01		^0.01
	Replace		^0.5	InSig		
Hot Water Heater					---	---
Insulation		^0.5	^0.01	^0.01	InSig	Ln
Lighting		Ln				

For six of the sixteen EEM investment series found to be significant, no transformation was indicated. Five of the six encompass the entirety of the significant coefficients for EEM investments in air conditioning, doors & windows, and hot water heaters. Thus the results of this analysis do not indicate diminishing marginal returns for EEM investments in these categories. The remaining non-transformed series is new heat pump investment in the electric heating degree day regression. However in two other instances, electric cooling degree days and natural gas heating degree days, a transformation was indicated. Thus, in the other five EEM investment series, furnace, new heat pump, replacement heat pump, insulation, and lighting, the regression results indicate a diminishing marginal return relative to each additional dollar invested.

Chapter IX - Conclusion

In evaluating measures of cost effectiveness of DSM programs, one must be aware of the potential biases of the analytical techniques employed. Two of these potential biases have been discussed herein. The first is the free-rider problem. LK proposes a method to more accurate measure the effects of DSM spending. Others have used the LK method and posited potential improvements. However, the base assumption underlying the LK method appears to be sound. However, this method does not account for impacts external to the DSM program industry. One of which is the free-driver impact as discussed by GNP. Other are the effects of reductions in CO_2 and related emissions as well as the economic effects related to the sale and installation of EEMs.

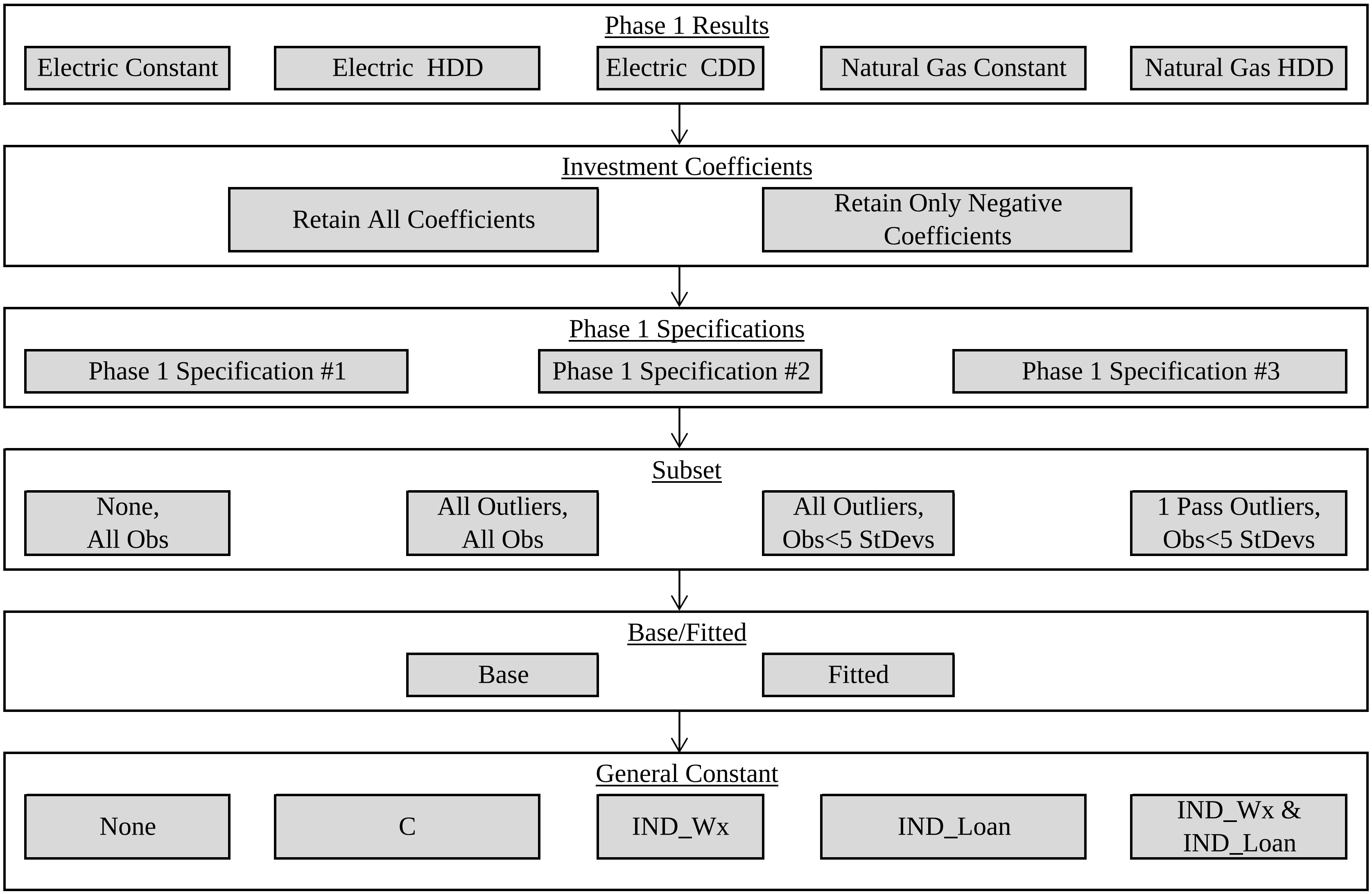
This analysis sought to quantify an estimate of the change in behavior relative to NEO's DSM program. While the estimated behavioral impact for low-income Nebraskans participating in the NEO's weatherization programs appears quite large, b = 0.8085, the behavioral impact estimated for the NEO's Loan Program, b = 0.2254, is in line with 20%, b = 0.20, estimated response relative to increased automobile efficiency cited by LK. The behavioral response estimated for the NEO's weatherization program could be evidence low-income energy consumers are sacrificing comfort for other necessary goods.

The differences in the observed behavioral response between participants in the NEO's Weatherization and Loan programs could be attributed to two factors under the assumption that those participating in the weatherization program have lower incomes. One, lower income households may have historically forgone comfort in order to meet other needs. Second, participants in the weatherization program have no cost associated with their DSM investments, while those participating in the loan program generally bear half the cost. Thus, participant in the weatherization program may experience a larger income effect because there is not offsetting investment costs. This may provide some evidence of comfort being an ordinary good as evidenced by a positive income effect.

The evidence regarding the returns to scale of DSM investments is mixed. Three of the investment series do not indicate declining returns to scale. Those categories are air conditioning, doors & windows, and hot water heaters. The other five investment series, furnace, heat pump (new and replacement), insulation, and lighting, do indicate evidence of declining returns to scale.

However, the estimates contained herein are based on data which is significantly smaller in scope and scale that estimates in other areas of DSM analysis. This analysis only includes DSM expenditures for a single year, does not include data on utility funded DSM programs, and encompasses only a portion of a single state. Additional, obtaining accurate billing data from energy providers was difficult. Data for only 339 (electric usage) and 187 (natural gas) properties could be reliably obtained. These properties account for only 0.04% and 0.02% of the estimated 800,000 total households in the state, based on the 2010 United State Census.

Appendix A
Phase 2 Regressions Map



Appendix B.1
Fitting and General Behavioral Effect
(Dep Var - Electric Constant , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
DW$	0.0043	0.3129			
FURN$	-0.0027	0.8449			
INSL$	-0.0281	0.0691	INSL$	-0.0230	0.1067
LITE$	1.8908	0.2296			
AC$	-0.0138	0.4969			
Out_Wx_Neg	-2,513	0.0000	Out_Wx_Neg	-2,493	0.0000
Out_Loan_Neg	-1,906	0.0000	Out_Loan_Neg	-1,889	0.0000
Out_Wx_Pos	1,954	0.0000	Out_Wx_Pos	2,001	0.0000
Out_Loan_Pos	1,322	0.0000	Out_Loan_Pos	1,328	0.0000
Akaike info criterion		15.1175	Akaike info criterion		15.0995

Variable	Coeff	Prob.	Variable	Coeff	Prob.
C	99.63	0.0260	C	86.14	0.0042
DW$	-0.0034	0.5416			
FURN$	-0.0187	0.2550			
INSL$	-0.0356	0.0496	(INSL$)^0.5	-3.1098	0.0479
LITE$	-1.0437	0.6532			
AC$	-0.0256	0.2105	AC$	-0.0350	0.0863
Out_Wx_Neg	-2,555	0.0000	Out_Wx_Neg	-2,564	0.0000
Out_Loan_Neg	-1,967	0.0000	Out_Loan_Neg	-1,960	0.0000
Out_Wx_Pos	1,980	0.0000	Out_Wx_Pos	1,959	0.0000
Out_Loan_Pos	1,249	0.0000	Out_Loan_Pos	1,242	0.0000
Akaike info criterion		15.1056	Akaike info criterion		15.0905

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	161.59	0.0114	IND_WX	360.15	0.0017
DW$	0.0045	0.2969			
FURN$	-0.0068	0.6262			
INSL$	-0.0414	0.0645	(INSL$)^0.5	-5.3332	0.0196
LITE$	-4.3198	0.1983	LN_LITE$	-80.24	0.0174
AC$	-0.0122	0.5448			
Out_Wx_Neg	-2,599	0.0000	Out_Wx_Neg	-2,680	0.0000
Out_Loan_Neg	-1,901	0.0000	Out_Loan_Neg	-1,857	0.0000
Out_Wx_Pos	1,946	0.0000	Out_Wx_Pos	1,957	0.0000
Out_Loan_Pos	1,325	0.0000	Out_Loan_Pos	1,328	0.0000
Akaike info criterion		15.1006	Akaike info criterion		15.0530 ***

Appendix B.1
Fitting and General Behavioral Effect
(Dep Var - Electric Constant , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation

Variable	Coeff	Prob.
IND_LOAN	33.40	0.5170
DW$	0.0017	0.7845
FURN$	-0.0072	0.6571
INSL$	-0.0279	0.0669
LITE$	2.1907	0.1804
AC$	-0.0180	0.3790
Out_Wx_Neg	-2,509	0.0000
Out_Loan_Neg	-1,928	0.0000
Out_Wx_Pos	1,964	0.0000
Out_Loan_Pos	1,297	0.0000
Akaike info criterion		15.1221

Variable	Coeff	Prob.
IND_WX	167.39	0.0100
IND_LOAN	48.78	0.3549
DW$	0.0006	0.9177
FURN$	-0.0135	0.4187
INSL$	-0.0415	0.0600
LITE$	-4.1045	0.2211
AC$	-0.0184	0.3673
Out_Wx_Neg	-2,597	0.0000
Out_Loan_Neg	-1,932	0.0000
Out_Wx_Pos	1,961	0.0000
Out_Loan_Pos	1,289	0.0000
Akaike info criterion		15.1038

Fitted Equation

Variable	Coeff	Prob.
IND_LOAN	19.91	0.5285
INSL$	-0.0238	0.0960
Out_Wx_Neg	-2,492	0.0000
Out_Loan_Neg	-1,908	0.0000
Out_Wx_Pos	2,002	0.0000
Out_Loan_Pos	1,308	0.0000
Akaike info criterion		15.1044

Variable	Coeff	Prob.
IND_WX	399.65	0.0019
IND_LOAN	55.86	0.1515
(FURN$)^0.01	-80.72	0.1459
(INSL$)^0.5	-5.5761	0.0159
LN_LITE$	-73.24	0.0221
Out_Wx_Neg	-2,707	0.0000
Out_Loan_Neg	-1,911	0.0000
Out_Wx_Pos	1,967	0.0000
Out_Loan_Pos	1,290	0.0000
Akaike info criterion		15.0546

Appendix B.2
Fitting and General Behavioral Effect
(Dep Var - Electric HDD , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
DW$	-0.0000	0.2764			
FURN$	-0.0000	0.8174			
INSL$	-0.0000	0.8615	(INSL$)^0.01	-0.0605	0.0354
HP$	0.0000	0.0010	HP$	0.0000	0.0005
CURRHP$	-0.0001	0.0001	(CURRHP$)^0.5	-0.0067	0.0000
Out_Wx_Neg	-2.4749	0.0005	Out_Wx_Neg	-2.4188	0.0007
Out_Loan_Neg	-2.0515	0.0000	Out_Loan_Neg	-2.0500	0.0000
Out_Wx_Pos	3.6845	0.0124	Out_Wx_Pos	3.7359	0.0109
Out_Loan_Pos	2.3264	0.0000	Out_Loan_Pos	2.2771	0.0000
Akaike info criterion		1.5216	Akaike info criterion		1.5059

Variable	Coeff	Prob.	Variable	Coeff	Prob.
C	0.0303	0.4343	C	0.1730	0.0157
DW$	-0.0000	0.1994	DW$	-0.0000	0.0234
FURN$	-0.0000	0.5290	(FURN$)^0.01	-0.0889	0.1026
INSL$	-0.0000	0.6741	(INSL$)^0.01	-0.1609	0.0032
HP$	0.0000	0.0022	HP$	0.0000	0.0784
CURRHP$	-0.0001	0.0001	LN_CURRHP$	-0.0720	0.0000
Out_Wx_Neg	-2.4882	0.0005	Out_Wx_Neg	-2.3876	0.0008
Out_Loan_Neg	-2.0650	0.0000	Out_Loan_Neg	-2.1016	0.0000
Out_Wx_Pos	3.6764	0.0125	Out_Wx_Pos	3.7784	0.0103
Out_Loan_Pos	2.3191	0.0000	Out_Loan_Pos	2.2330	0.0000
Akaike info criterion		1.5260	Akaike info criterion		1.5013

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	-0.0062	0.8735	IND_WX	0.1928	0.0836
DW$	-0.0000	0.2801			
FURN$	-0.0000	0.8618			
INSL$	-0.0000	0.9182	(INSL$)^0.01	-0.2370	0.0305
HP$	0.0000	0.0011	HP$	0.0000	0.0005
CURRHP$	-0.0001	0.0001	(CURRHP$)^0.5	-0.0067	0.0000
Out_Wx_Neg	-2.4702	0.0005	Out_Wx_Neg	-2.4248	0.0007
Out_Loan_Neg	-2.0506	0.0000	Out_Loan_Neg	-2.0500	0.0000
Out_Wx_Pos	3.6882	0.0124	Out_Wx_Pos	3.7320	0.0111
Out_Loan_Pos	2.3267	0.0000	Out_Loan_Pos	2.2771	0.0000
Akaike info criterion		1.5275	Akaike info criterion		1.4983 ***

Appendix B.2

Fitting and General Behavioral Effect

(Dep Var - Electric HDD , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_LOAN	0.0891	0.1243	IND_LOAN	0.0625	0.2380
DW$	-0.0000	0.0860	DW$	-0.0000	0.1570
FURN$	-0.0000	0.2848			
INSL$	-0.0000	0.9576	(INSL$)^0.01	-0.0524	0.0742
HP$	0.0000	0.0184	HP$	0.0000	0.0163
CURRHP$	-0.0001	0.0001	(CURRHP$)^0.5	-0.0068	0.0000
Out_Wx_Neg	-2.4472	0.0005	Out_Wx_Neg	-2.4263	0.0007
Out_Loan_Neg	-2.0777	0.0000	Out_Loan_Neg	-2.0543	0.0000
Out_Wx_Pos	3.7141	0.0118	Out_Wx_Pos	3.7337	0.0111
Out_Loan_Pos	2.3092	0.0000	Out_Loan_Pos	2.2880	0.0000
Akaike info criterion		1.5224	Akaike info criterion		1.5120

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	0.0098	0.8120	IND_WX	0.2580	0.0374
IND_LOAN	0.0928	0.1322	IND_LOAN	0.1371	0.0414
DW$	-0.0000	0.0898	DW$	-0.0000	0.0504
FURN$	-0.0000	0.3055	(FURN$)^0.01	-0.0877	0.0999
INSL$	-0.0000	0.8815	(INSL$)^0.01	-0.2414	0.0237
HP$	0.0000	0.0194	HP$	0.0000	0.0368
CURRHP$	-0.0001	0.0001	LN_CURRHP$	-0.0710	0.0000
Out_Wx_Neg	-2.4533	0.0005	Out_Wx_Neg	-2.3892	0.0008
Out_Loan_Neg	-2.0803	0.0000	Out_Loan_Neg	-2.0976	0.0000
Out_Wx_Pos	3.7095	0.0119	Out_Wx_Pos	3.7763	0.0105
Out_Loan_Pos	2.3080	0.0000	Out_Loan_Pos	2.2368	0.0000
Akaike info criterion		1.5282	Akaike info criterion		1.5032

Appendix B.3
Fitting and General Behavioral Effect
(Dep Var - Electric CDD , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
DW$	0.0000	0.9855			
FURN$	-0.0001	0.0207	(FURN$)^0.5	-0.0047	0.0515
INSL$	0.0000	0.7835			
AC$	-0.0001	0.0957	AC$	-0.0001	0.0778
HP$	-0.0000	0.4888	(HP$)^0.01	-0.2214	0.1846
CURRHP$	-0.0000	0.8482			
Out_Wx_Neg	-3.7795	0.0000	Out_Wx_Neg	-3.7297	0.0000
Out_Loan_Neg	-4.0946	0.0000	Out_Loan_Neg	-4.0199	0.0000
Out_Wx_Pos	6.7696	0.0009	Out_Wx_Pos	6.8013	0.0007
Out_Loan_Pos	3.2001	0.0000	Out_Loan_Pos	3.2441	0.0000
Akaike info criterion		3.0543	Akaike info criterion		3.0303

Variable	Coeff	Prob.	Variable	Coeff	Prob.	
C	0.1280	0.1211	C	0.4489	0.0028	
DW$	-0.0000	0.5004	DW$	-0.0000	0.0557	
FURN$	-0.0001	0.0068	(FURN$)^0.01	-0.4249	0.0004	
INSL$	-0.0000	0.9778	(INSL$)^0.01	-0.1884	0.1931	
AC$	-0.0001	0.0505	AC$	-0.0002	0.0022	
HP$	-0.0000	0.2879	(HP$)^0.01	-0.5646	0.0027	
CURRHP$	-0.0000	0.7484				
Out_Wx_Neg	-3.8432	0.0000	Out_Wx_Neg	-3.9420	0.0000	
Out_Loan_Neg	-4.1071	0.0000	Out_Loan_Neg	-3.9880	0.0000	
Out_Wx_Pos	6.6733	0.0010	Out_Wx_Pos	6.5889	0.0004	
Out_Loan_Pos	3.1766	0.0000	Out_Loan_Pos	3.1918	0.0000	
Akaike info criterion		3.0547	Akaike info criterion		3.0202	***

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	0.1118	0.1839	IND_WX	0.4925	0.0065
DW$	-0.0000	0.9821			
FURN$	-0.0001	0.0106	(FURN$)^0.01	-0.3520	0.0034
INSL$	-0.0000	0.9802	(INSL$)^0.01	-0.2954	0.0951
AC$	-0.0001	0.1199	AC$	-0.0001	0.1320
HP$	-0.0000	0.5487	(HP$)^0.01	-0.1851	0.2564
CURRHP$	-0.0000	0.8146			
Out_Wx_Neg	-3.8366	0.0000	Out_Wx_Neg	-3.9016	0.0000
Out_Loan_Neg	-4.0917	0.0000	Out_Loan_Neg	-4.0138	0.0000
Out_Wx_Pos	6.6764	0.0010	Out_Wx_Pos	6.5559	0.0004
Out_Loan_Pos	3.2497	0.0000	Out_Loan_Pos	3.5642	0.0000
Akaike info criterion		3.0562	Akaike info criterion		3.0241

Appendix B.3
Fitting and General Behavioral Effect
(Dep Var - Electric CDD , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_LOAN	0.0665	0.7146	IND_LOAN	-0.1393	0.2237
DW$	-0.0000	0.8081	LN_DW$	0.0277	0.0254
FURN$	-0.0001	0.0251	LN_FURN$	-0.0461	0.0019
INSL$	0.0000	0.7706			
AC$	-0.0001	0.1018			
HP$	-0.0000	0.4186			
CURRHP$	-0.0000	0.8178			
Out_Wx_Neg	-3.7787	0.0000	Out_Wx_Neg	-3.9178	0.0000
Out_Loan_Neg	-4.1029	0.0000	Out_Loan_Neg	-4.1422	0.0000
Out_Wx_Pos	6.7750	0.0009	Out_Wx_Pos	6.7294	0.0005
Out_Loan_Pos	3.1584	0.0000	Out_Loan_Pos	3.1457	0.0000
Akaike info criterion		3.0596	Akaike info criterion		3.0279

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	0.1302	0.1242	IND_WX	0.5105	0.0055
IND_LOAN	0.1197	0.5163	IND_LOAN	0.1526	0.2170
DW$	-0.0000	0.6378			
FURN$	-0.0001	0.0101	(FURN$)^0.01	-0.3631	0.0039
INSL$	-0.0000	0.9718	(INSL$)^0.01	-0.3052	0.0883
AC$	-0.0001	0.0917	(AC$)^0.01	-0.3716	0.1124
HP$	-0.0000	0.3734	(HP$)^0.01	-0.3177	0.1021
CURRHP$	-0.0000	0.7544			
Out_Wx_Neg	-3.8444	0.0000	Out_Wx_Neg	-3.9090	0.0000
Out_Loan_Neg	-4.1060	0.0000	Out_Loan_Neg	-4.0647	0.0000
Out_Wx_Pos	6.6708	0.0010	Out_Wx_Pos	6.5492	0.0003
Out_Loan_Pos	3.1828	0.0000	Out_Loan_Pos	3.4222	0.0000
Akaike info criterion		3.0605	Akaike info criterion		3.0241

Appendix B.4
Fitting and General Behavioral Effect
(Dep Var - Natural Gas Constant , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation			
Variable	Coeff	Prob.	Variable	Coeff	Prob.	
DW$	-0.0007	0.0001	DW$	-0.0006	0.0002	
FURN$	-0.0006	0.3440				
INSL$	0.0011	0.0833				
HWH$	0.0073	0.0204	HWH$	0.0068	0.0269	
Out_Wx_Neg	-69.39	0.0000	Out_Wx_Neg	-68.93	0.0000	
Out_Loan_Neg	-53.47	0.0000	Out_Loan_Neg	-54.84	0.0000	
Out_Wx_Pos	75.42	0.0000	Out_Wx_Pos	76.43	0.0000	
Out_Loan_Pos	73.76	0.0000	Out_Loan_Pos	71.01	0.0000	
Akaike info criterion		8.4782	Akaike info criterion		8.4770	***

Variable	Coeff	Prob.	Variable	Coeff	Prob.
C	2.2548	0.2545	C	3.5840	0.0983
DW$	-0.0009	0.0002	DW$	-0.0010	0.0001
FURN$	-0.0010	0.1608	(FURN$)^0.5	-0.0801	0.1209
INSL$	0.0010	0.1488			
HWH$	0.0062	0.0697	HWH$	0.0060	0.0813
Out_Wx_Neg	-71.58	0.0000	Out_Wx_Neg	-72.50	0.0000
Out_Loan_Neg	-53.62	0.0000	Out_Loan_Neg	-53.94	0.0000
Out_Wx_Pos	73.45	0.0000	Out_Wx_Pos	73.85	0.0000
Out_Loan_Pos	73.87	0.0000	Out_Loan_Pos	72.19	0.0000
Akaike info criterion		8.4815	Akaike info criterion		8.4803

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	2.3281	0.2310	IND_WX	2.4063	0.1917
DW$	-0.0007	0.0000	DW$	-0.0007	0.0001
FURN$	-0.0007	0.2530			
INSL$	0.0010	0.1811			
HWH$	0.0063	0.0528	HWH$	0.0055	0.0923
Out_Wx_Neg	-71.64	0.0000	Out_Wx_Neg	-71.33	0.0000
Out_Loan_Neg	-53.11	0.0000	Out_Loan_Neg	-54.63	0.0000
Out_Wx_Pos	73.29	0.0000	Out_Wx_Pos	74.03	0.0000
Out_Loan_Pos	74.51	0.0000	Out_Loan_Pos	71.04	0.0000
Akaike info criterion		8.4816	Akaike info criterion		8.4789

Appendix B.4
Fitting and General Behavioral Effect
(Dep Var - Natural Gas Constant , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_LOAN	0.1886	0.9408	IND_LOAN	-0.7356	0.7307
DW$	-0.0007	0.0213	DW$	-0.0006	0.0439
FURN$	-0.0006	0.3662	LN_HWH$	1.0166	0.0531
INSL$	0.0011	0.0845			
HWH$	0.0073	0.0480			
Out_Wx_Neg	-69.39	0.0000	Out_Wx_Neg	-69.39	0.0000
Out_Loan_Neg	-53.51	0.0000	Out_Loan_Neg	-54.46	0.0000
Out_Wx_Pos	75.42	0.0000	Out_Wx_Pos	76.00	0.0000
Out_Loan_Pos	73.71	0.0000	Out_Loan_Pos	71.70	0.0000
Akaike info criterion		8.4889	Akaike info criterion		8.4867

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	2.7117	0.1923	IND_WX	4.0954	0.0671
IND_LOAN	1.3631	0.6480	IND_LOAN	2.2951	0.4742
DW$	-0.0008	0.0047	DW$	-0.0009	0.0051
FURN$	-0.0009	0.2151	(FURN$)^0.5	-0.0713	0.1809
INSL$	0.0009	0.1839			
HWH$	0.0061	0.0724	HWH$	0.0058	0.0868
Out_Wx_Neg	-72.02	0.0000	Out_Wx_Neg	-73.02	0.0000
Out_Loan_Neg	-53.35	0.0000	Out_Loan_Neg	-53.56	0.0000
Out_Wx_Pos	73.00	0.0000	Out_Wx_Pos	73.21	0.0000
Out_Loan_Pos	74.26	0.0000	Out_Loan_Pos	72.91	0.0000
Akaike info criterion		8.4909	Akaike info criterion		8.4886

Appendix B.5
Fitting and General Behavioral Effect
(Dep Var - Natural Gas HDD , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
DW$	-0.0000	0.9095			
FURN$	-0.0000	0.0020	(FURN$)^0.5	-0.0002	0.0002
HP$	-0.0000	0.0557	(HP$)^0.01	-0.0164	0.0028
HWH$	-0.0000	0.0006	HWH$	-0.0000	0.0099
INSL$	-0.0000	0.0338	LN_INSL$	-0.0015	0.0004
Out_Wx_Neg	-0.0843	0.0000	Out_Wx_Neg	-0.0777	0.0000
Out_Loan_Neg	-0.1112	0.0000	Out_Loan_Neg	-0.1191	0.0000
Out_Wx_Pos	0.0995	0.0000	Out_Wx_Pos	0.1019	0.0000
Out_Loan_Pos	0.2072	0.0000	Out_Loan_Pos	0.2213	0.0000
Akaike info criterion		-4.5825	Akaike info criterion		-4.7035 ***

Variable	Coeff	Prob.	Variable	Coeff	Prob.
C	-0.0114	0.0007	C	-0.0028	0.2765
DW$	0.0000	0.0185			
FURN$	-0.0000	0.1671	LN_FURN$	-0.0015	0.0015
HP$	-0.0000	0.1580	(HP$)^0.01	-0.0148	0.0082
HWH$	-0.0000	0.0237	HWH$	-0.0000	0.0078
INSL$	-0.0000	0.0893	(INSL$)^0.5	-0.0002	0.0253
Out_Wx_Neg	-0.0807	0.0000	Out_Wx_Neg	-0.0808	0.0000
Out_Loan_Neg	-0.1099	0.0000	Out_Loan_Neg	-0.1186	0.0000
Out_Wx_Pos	0.0997	0.0000	Out_Wx_Pos	0.1030	0.0000
Out_Loan_Pos	0.2125	0.0000	Out_Loan_Pos	0.2232	0.0000
Akaike info criterion		-4.6646	Akaike info criterion		-4.6949

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	-0.0097	0.0017	IND_WX	-0.0087	0.0058
DW$	0.0000	0.9319			
FURN$	-0.0000	0.0078	(FURN$)^0.5	-0.0002	0.0005
HP$	-0.0000	0.0365	(HP$)^0.01	-0.0167	0.0025
HWH$	-0.0000	0.0286	HWH$	-0.0000	0.0347
INSL$	-0.0000	0.0639	INSL$	-0.0000	0.0548
Out_Wx_Neg	-0.0780	0.0000	Out_Wx_Neg	-0.0786	0.0000
Out_Loan_Neg	-0.1120	0.0000	Out_Loan_Neg	-0.1196	0.0000
Out_Wx_Pos	0.1052	0.0000	Out_Wx_Pos	0.1050	0.0000
Out_Loan_Pos	0.2064	0.0000	Out_Loan_Pos	0.2213	0.0000
Akaike info criterion		-4.6344	Akaike info criterion		-4.6973

Appendix B.5
Fitting and General Behavioral Effect
(Dep Var - Natural Gas HDD , Phase 1 Spec #3, All Outliers, All Observations)

Base Equation			Fitted Equation		
Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_LOAN	-0.0045	0.3388	IND_LOAN	-0.0014	0.5608
DW$	0.0000	0.4765			
FURN$	-0.0000	0.0304	(FURN$)^0.5	-0.0002	0.0013
HP$	-0.0000	0.1380	(HP$)^0.01	-0.0157	0.0057
HWH$	-0.0000	0.0004	HWH$	-0.0000	0.0094
INSL$	-0.0000	0.0429	LN_INSL$	-0.0015	0.0003
Out_Wx_Neg	-0.0858	0.0000	Out_Wx_Neg	-0.0781	0.0000
Out_Loan_Neg	-0.1103	0.0000	Out_Loan_Neg	-0.1186	0.0000
Out_Wx_Pos	0.0970	0.0000	Out_Wx_Pos	0.1014	0.0000
Out_Loan_Pos	0.2097	0.0000	Out_Loan_Pos	0.2213	0.0000
Akaike info criterion		-4.5787	Akaike info criterion		-4.6942

Variable	Coeff	Prob.	Variable	Coeff	Prob.
IND_WX	-0.0120	0.0005	IND_WX	-0.0071	0.0715
IND_LOAN	-0.0099	0.0459	IND_LOAN	-0.0019	0.4713
DW$	0.0000	0.0965			
FURN$	-0.0000	0.1735	(FURN$)^0.5	-0.0002	0.0037
HP$	-0.0000	0.1544	(HP$)^0.01	-0.0159	0.0052
HWH$	-0.0000	0.0307	HWH$	-0.0000	0.0296
INSL$	-0.0000	0.0935	(INSL$)^0.5	-0.0001	0.1249
Out_Wx_Neg	-0.0799	0.0000	Out_Wx_Neg	-0.0784	0.0000
Out_Loan_Neg	-0.1102	0.0000	Out_Loan_Neg	-0.1187	0.0000
Out_Wx_Pos	0.1010	0.0000	Out_Wx_Pos	0.1038	0.0000
Out_Loan_Pos	0.2116	0.0000	Out_Loan_Pos	0.2213	0.0000
Akaike info criterion		-4.6554	Akaike info criterion		-4.6930

Appendix C-1

Phase 1 Specifications Comparisons (Only Significant Negative Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(2), Lite(0)

Dependent Variable: ELEC_CONST
Included observations: 339
Wx(158,-1,1) & Loan(181,-3,1)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	-344.26	0.0320
(INSL$)^0.01	341.94	0.0252
AC$	-0.0406	0.0206
Out_Wx_Neg	-4,839	0.0000
Out_Loan_Neg	-2,406	0.0000
Out_Wx_Pos	5,417	0.0000
Out_Loan_Pos	1,487	0.0000

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(1),
Sig Coeffs - Insl(2), Lite(1)

Dependent Variable: ELEC_CONST
Included observations: 339
Wx(158,-1,3) & Loan(181,-4,0)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	-59.34	0.1556
(INSL$)^0.01	195.00	0.0100
(LITE$)^0.5	-39.97	0.0370
Out_Wx_Neg	-5,008	0.0000
Out_Loan_Neg	-2,410	0.0000
Out_Wx_Pos	3,539	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(2), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(1)

Dependent Variable: ELEC_CONST
Included observations: 339
Wx(158,-11,4) & Loan(181,-7,5)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	360.15	0.0017
(INSL$)^0.5	-5.3332	0.0196
LN_LITE$	-80.24	0.0174
Out_Wx_Neg	-2,680	0.0000
Out_Loan_Neg	-1,857	0.0000
Out_Wx_Pos	1,957	0.0000
Out_Loan_Pos	1,328	0.0000

Appendix C-1

Phase 1 Specifications Comparisons (Only Significant Negative Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(2), Lite(0)

Dependent Variable: ELEC_CDD
Included observations: 339
Wx(158,-1,2) & Loan(181,-7,0)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	0.2223	0.0060
(FURN$)^0.01	-0.3598	0.0025
(AC$)^0.01	-0.4807	0.0205
LN_HP$	-0.0517	0.0091
Out_Wx_Neg	-3.9520	0.0000
Out_Loan_Neg	-4.1611	0.0000
Out_Wx_Pos	6.6719	0.0006

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(1),
Sig Coeffs - Insl(2), Lite(1)

Dependent Variable: ELEC_CDD
Included observations: 339
Wx(158,-1,1) & Loan(181,-7,0)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	0.1829	0.0204
(FURN$)^0.01	-0.3168	0.0079
(AC$)^0.5	-0.0077	0.0256
(HP$)^0.01	-0.4164	0.0075
Out_Wx_Neg	-3.8972	0.0000
Out_Loan_Neg	-4.2402	0.0000
Out_Wx_Pos	9.1074	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(2), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(1)

Dependent Variable: ELEC_CDD
Included observations: 339
Wx(158,-1,2) & Loan(181,-8,1)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	0.4489	0.0028
DW$	-0.0000	0.0557
(FURN$)^0.01	-0.4249	0.0004
(INSL$)^0.01	-0.1884	0.1931
AC$	-0.0002	0.0022
(HP$)^0.01	-0.5646	0.0027
Out_Wx_Neg	-3.9420	0.0000
Out_Loan_Neg	-3.9880	0.0000
Out_Wx_Pos	6.5889	0.0004
Out_Loan_Pos	3.1918	0.0000

Appendix C-1

Phase 1 Specifications Comparisons (Only Significant Negative Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(0), Furn(2), Sig Coeffs - HP(4), HWH(2), Sig Coeffs - Insl(2), Lite(0)

Dependent Variable: ELEC_HDD
Included observations: 339
Wx(158,-3,2) & Loan(181,-1,11)
White heteroskedasticity-consistent standard errors & covariance

Variable	Coeff	Prob.
HP$	0.0000	0.0029
(CURRHP$)^0.01	-0.3650	0.0022
Out_Wx_Neg	-2.2439	0.0000
Out_Loan_Neg	-1.2960	0.0000
Out_Wx_Pos	1.8963	0.0000
Out_Loan_Pos	1.9628	0.0000

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(0), Furn(2), Sig Coeffs - HP(4), HWH(1), Sig Coeffs - Insl(2), Lite(1)

Dependent Variable: ELEC_HDD
Included observations: 339
Wx(158,-2,2) & Loan(181,-1,9)
White heteroskedasticity-consistent standard errors & covariance

Variable	Coeff	Prob.
HP$	0.0000	0.0001
(CURRHP$)^0.01	-0.4171	0.0001
Out_Wx_Neg	-2.1963	0.0016
Out_Loan_Neg	-1.3608	0.0000
Out_Wx_Pos	2.5143	0.0004
Out_Loan_Pos	2.0395	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(2), Furn(2), Sig Coeffs - HP(4), HWH(2), Sig Coeffs - Insl(4), Lite(1)

Dependent Variable: ELEC_HDD
Included observations: 339
Wx(158,-2,3) & Loan(181,-1,6)
White heteroskedasticity-consistent standard errors & covariance

Variable	Coeff	Prob.
IND_WX	0.1928	0.0836
(INSL$)^0.01	-0.2370	0.0305
HP$	0.0000	0.0005
(CURRHP$)^0.5	-0.0067	0.0000
Out_Wx_Neg	-2.4248	0.0007
Out_Loan_Neg	-2.0500	0.0000
Out_Wx_Pos	3.7320	0.0111
Out_Loan_Pos	2.2771	0.0000

Appendix C-1

Phase 1 Specifications Comparisons (Only Significant Negative Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(2), Lite(0)

Dependent Variable: NG_CONST
Included observations: 187
Wx(85,-2,3) & Loan(102,-5,4)

Variable	Coeff	Prob.
HWH$	0.0044	0.1084
Out_Wx_Neg	-47.82	0.0000
Out_Loan_Neg	-49.38	0.0000
Out_Wx_Pos	62.39	0.0000
Out_Loan_Pos	66.23	0.0000

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(1),
Sig Coeffs - Insl(2), Lite(1)

Dependent Variable: NG_CONST
Included observations: 187
Wx(85,-2,3) & Loan(102,-1,5)

Variable	Coeff	Prob.
IND_WX	3.0477	0.1212
Out_Wx_Neg	-58.16	0.0000
Out_Loan_Neg	-94.51	0.0000
Out_Wx_Pos	72.76	0.0000
Out_Loan_Pos	77.44	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(2), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(1)

Dependent Variable: NG_CONST
Included observations: 187
Wx(85,-1,2) & Loan(102,-2,4)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
DW$	-0.0006	0.0002
HWH$	0.0068	0.0269
Out_Wx_Neg	-68.93	0.0000
Out_Loan_Neg	-54.84	0.0000
Out_Wx_Pos	76.43	0.0000
Out_Loan_Pos	71.01	0.0000

Appendix C-1

Phase 1 Specifications Comparisons (Only Significant Negative Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(2), Lite(0)

Dependent Variable: NG_HDD
Included observations: 187
Wx(85,0,1) & Loan(102,-3,2)
White heteroskedasticity-consistent standard errors & covariance

Variable	Coeff	Prob.
IND_LOAN	-0.0053	0.0371
FURN$	-0.0000	0.0000
HP$	-0.0000	0.1881
HWH$	-0.0000	0.1714
LN_INSL$	-0.0023	0.0000
Out_Loan_Neg	-0.1199	0.0000
Out_Wx_Pos	0.0877	0.0000
Out_Loan_Pos	0.2113	0.0174

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(0), Furn(2),
Sig Coeffs - HP(4), HWH(1),
Sig Coeffs - Insl(2), Lite(1)

Dependent Variable: NG_HDD
Included observations: 187
Wx(85,-4,2) & Loan(102,-4,1)
White heteroskedasticity-consistent standard errors & covariance

Variable	Coeff	Prob.
C	-0.0042	0.0293
(FURN$)^0.5	-0.0002	0.0000
HP$	-0.0000	0.0000
HWH$	-0.0000	0.0024
(INSL$)^0.5	-0.0002	0.0050
Out_Wx_Neg	-0.0797	0.0000
Out_Loan_Neg	-0.0972	0.0000
Out_Wx_Pos	0.0861	0.0000
Out_Loan_Pos	0.3295	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(2), Furn(2),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(1)

Dependent Variable: NG_HDD
Included observations: 187
Wx(85,-3,2) & Loan(102,-4,1)
White heteroskedasticity-consistent standard errors & covariance

Variable	Coeff	Prob.
(FURN$)^0.5	-0.0002	0.0002
(HP$)^0.01	-0.0164	0.0028
HWH$	-0.0000	0.0099
LN_INSL$	-0.0015	0.0004
Out_Wx_Neg	-0.0777	0.0000
Out_Loan_Neg	-0.1191	0.0000
Out_Wx_Pos	0.1019	0.0000
Out_Loan_Pos	0.2213	0.0000

Appendix C-2

Phase 1 Specifications Comparisons (All SIgnificant Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(2), Furn(3), Sig Coeffs - HP(3), HWH(1), Sig Coeffs - Insl(3), Lite(0)

Dependent Variable: ELEC_CONST
Included observations: 339
Wx(158,-1,1) & Loan(181,-3,1)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	-506.28	0.0052
IND_LOAN	-173.53	0.0125
LN_DW$	23.31	0.0053
(FURN$)^0.01	161.81	0.0104
(INSL$)^0.01	296.02	0.0332
AC$	-0.0342	0.1072
Out_Wx_Neg	-4,911	0.0000
Out_Loan_Neg	-2,424	0.0000
Out_Wx_Pos	5,285	0.0000
Out_Loan_Pos	1,661	0.0000

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(3), Sig Coeffs - HP(4), HWH(2), Sig Coeffs - Insl(4), Lite(0)

Dependent Variable: ELEC_CONST
Included observations: 339
Wx(158,-1,3) & Loan(181,-4,0)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	-463.74	0.0091
(INSL$)^0.01	455.70	0.0071
Out_Wx_Neg	-5,061	0.0000
Out_Loan_Neg	-2,540	0.0000
Out_Wx_Pos	3,559	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(1), Sig Coeffs - HP(4), HWH(2), Sig Coeffs - Insl(5), Lite(1)

Dependent Variable: ELEC_CONST
Included observations: 339
Wx(158,-11,4) & Loan(181,-7,5)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	360.15	0.0017
(INSL$)^0.5	-5.3332	0.0196
LN_LITE$	-80.24	0.0174
Out_Wx_Neg	-2,680	0.0000
Out_Loan_Neg	-1,857	0.0000
Out_Wx_Pos	1,957	0.0000
Out_Loan_Pos	1,328	0.0000

Appendix C-2

Phase 1 Specifications Comparisons (All SIgnificant Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(2), Furn(3),
Sig Coeffs - HP(3), HWH(1),
Sig Coeffs - Insl(3), Lite(0)

Dependent Variable: ELEC_CDD
Included observations: 339
Wx(158,-1,2) & Loan(181,-7,0)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	0.2203	0.0064
(FURN$)^0.01	-0.3550	0.0029
(AC$)^0.01	-0.4834	0.0200
(HP$)^0.01	-0.4121	0.0095
Out_Wx_Neg	-3.9500	0.0000
Out_Loan_Neg	-4.1584	0.0000
Out_Wx_Pos	6.6712	0.0006

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(3),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(0)

Dependent Variable: ELEC_CDD
Included observations: 339
Wx(158,-1,1) & Loan(181,-7,0)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	0.1829	0.0204
(FURN$)^0.01	-0.3168	0.0079
(AC$)^0.5	-0.0077	0.0256
(HP$)^0.01	-0.4164	0.0075
Out_Wx_Neg	-3.8972	0.0000
Out_Loan_Neg	-4.2402	0.0000
Out_Wx_Pos	9.1074	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(1),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(5), Lite(1)

Dependent Variable: ELEC_CDD
Included observations: 339
Wx(158,-1,2) & Loan(181,-8,1)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	0.4489	0.0028
DW$	-0.0000	0.0557
(FURN$)^0.01	-0.4249	0.0004
(INSL$)^0.01	-0.1884	0.1931
AC$	-0.0002	0.0022
(HP$)^0.01	-0.5646	0.0027
Out_Wx_Neg	-3.9420	0.0000
Out_Loan_Neg	-3.9880	0.0000
Out_Wx_Pos	6.5889	0.0004
Out_Loan_Pos	3.1918	0.0000

Appendix C-2

Phase 1 Specifications Comparisons (All SIgnificant Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(2), Furn(3),
Sig Coeffs - HP(3), HWH(1),
Sig Coeffs - Insl(3), Lite(0)

Dependent Variable: ELEC_HDD
Included observations: 339
Wx(158,-3,2) & Loan(181,-1,11)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
HP$	0.0000	0.0029
(CURRHP$)^0.01	-0.3650	0.0022
Out_Wx_Neg	-2.2439	0.0000
Out_Loan_Neg	-1.2960	0.0000
Out_Wx_Pos	1.8963	0.0000
Out_Loan_Pos	1.9628	0.0000

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(3),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(0)

Dependent Variable: ELEC_HDD
Included observations: 339
Wx(158,-2,2) & Loan(181,-1,9)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
(DW$)^0.01	0.0503	0.1834
FURN$	0.0000	0.1716
(INSL$)^0.01	-0.0841	0.0526
HP$	0.0000	0.0005
(CURRHP$)^0.01	-0.3961	0.0003
Out_Wx_Neg	-2.1746	0.0016
Out_Loan_Neg	-1.4162	0.0000
Out_Wx_Pos	2.5080	0.0006
Out_Loan_Pos	2.0289	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(1),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(5), Lite(1)

Dependent Variable: ELEC_HDD
Included observations: 339
Wx(158,-2,3) & Loan(181,-1,6)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	0.1928	0.0836
(INSL$)^0.01	-0.2370	0.0305
HP$	0.0000	0.0005
(CURRHP$)^0.5	-0.0067	0.0000
Out_Wx_Neg	-2.4248	0.0007
Out_Loan_Neg	-2.0500	0.0000
Out_Wx_Pos	3.7320	0.0111
Out_Loan_Pos	2.2771	0.0000

Appendix C-2

Phase 1 Specifications Comparisons (All SIgnificant Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(2), Furn(3), Sig Coeffs - HP(3), HWH(1), Sig Coeffs - Insl(3), Lite(0)

Dependent Variable: NG_CONST
Included observations: 187
Wx(85,-2,3) & Loan(102,-5,4)

Variable	Coeff	Prob.
LN_INSL$	0.3221	0.1709
HWH$	0.0036	0.1972
Out_Wx_Neg	-50.09	0.0000
Out_Loan_Neg	-49.38	0.0000
Out_Wx_Pos	60.38	0.0000
Out_Loan_Pos	65.48	0.0000

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(3), Sig Coeffs - HP(4), HWH(2), Sig Coeffs - Insl(4), Lite(0)

Dependent Variable: NG_CONST
Included observations: 187
Wx(85,-2,3) & Loan(102,-1,5)

Variable	Coeff	Prob.
IND_WX	-11.34	0.0268
DW$	-0.0004	0.1201
(INSL$)^0.01	14.51	0.0028
HWH$	0.0056	0.1548
Out_Wx_Neg	-51.48	0.0001
Out_Loan_Neg	-94.51	0.0000
Out_Wx_Pos	77.17	0.0000
Out_Loan_Pos	77.69	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(1), Sig Coeffs - HP(4), HWH(2), Sig Coeffs - Insl(5), Lite(1)

Dependent Variable: NG_CONST
Included observations: 187
Wx(85,-1,2) & Loan(102,-2,4)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
DW$	-0.0007	0.0001
(INSL$)^0.01	2.7747	0.1260
HWH$	0.0057	0.0854
Out_Wx_Neg	-71.87	0.0000
Out_Loan_Neg	-54.54	0.0000
Out_Wx_Pos	73.49	0.0000
Out_Loan_Pos	71.05	0.0000

Appendix C-2

Phase 1 Specifications Comparisons (All SIgnificant Investment Coefficients)

Spec #1 (Ind ARMA, Sig Vars)
Sig Coeffs - AC(2), DW(2), Furn(3),
Sig Coeffs - HP(3), HWH(1),
Sig Coeffs - Insl(3), Lite(0)

Dependent Variable: NG_HDD
Included observations: 187
Wx(85,0,1) & Loan(102,-3,2)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	-0.0289	0.0001
IND_LOAN	-0.0216	0.0003
(DW$)^0.01	0.0204	0.0006
FURN$	-0.0000	0.0233
(INSL$)^0.5	-0.0003	0.0023
Out_Loan_Neg	-0.1306	0.0000
Out_Wx_Pos	0.0870	0.0000
Out_Loan_Pos	0.2201	0.0122

Spec #2 (Ind ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(3),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(4), Lite(0)

Dependent Variable: NG_HDD
Included observations: 187
Wx(85,-4,2) & Loan(102,-4,1)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
C	-0.0135	0.0016
(DW$)^0.01	0.0095	0.0242
FURN$	-0.0000	0.0097
HP$	-0.0000	0.0000
HWH$	-0.0000	0.0004
(INSL$)^0.5	-0.0003	0.0009
Out_Wx_Neg	-0.0792	0.0000
Out_Loan_Neg	-0.0949	0.0000
Out_Wx_Pos	0.0814	0.0000
Out_Loan_Pos	0.3308	0.0000

Spec #3 (All ARMA, All Vars)
Sig Coeffs - AC(1), DW(3), Furn(1),
Sig Coeffs - HP(4), HWH(2),
Sig Coeffs - Insl(5), Lite(1)

Dependent Variable: NG_HDD
Included observations: 187
Wx(85,-3,2) & Loan(102,-4,1)
White heteroskedasticity-consistent
standard errors & covariance

Variable	Coeff	Prob.
IND_WX	-0.0288	0.0000
IND_LOAN	-0.0189	0.0000
(DW$)^0.01	0.0192	0.0000
LN_HP$	-0.0014	0.0818
HWH$	-0.0000	0.0219
(INSL$)^0.5	-0.0002	0.0153
Out_Wx_Neg	-0.0829	0.0000
Out_Loan_Neg	-0.1094	0.0000
Out_Wx_Pos	0.0966	0.0000
Out_Loan_Pos	0.2223	0.0000

Appendix D

Comparison of All Significant and Only Significant Negative Coefficents Regression Results

All Outliers, All Obs, All Coeffs
Spec #3 (All ARMA, All Vars)

Dependent Variable: ELEC_CONST

Variable	Coeff	Prob.
IND_WX	360.15	0.0017
(INSL$)^0.5	-5.3332	0.0196
LN_LITE$	-80.24	0.0174
Out_Wx_Neg	-2,680	0.0000
Out_Loan_Neg	-1,857	0.0000
Out_Wx_Pos	1,957	0.0000
Out_Loan_Pos	1,328	0.0000

Dependent Variable: ELEC_CDD

Variable	Coeff	Prob.
C	0.4489	0.0028
DW$	-0.0000	0.0557
(FURN$)^0.01	-0.4249	0.0004
(INSL$)^0.01	-0.1884	0.1931
AC$	-0.0002	0.0022
(HP$)^0.01	-0.5646	0.0027
Out_Wx_Neg	-3.9420	0.0000
Out_Loan_Neg	-3.9880	0.0000
Out_Wx_Pos	6.5889	0.0004
Out_Loan_Pos	3.1918	0.0000

Dependent Variable: ELEC_HDD

Variable	Coeff	Prob.
IND_WX	0.1928	0.0836
(INSL$)^0.01	-0.2370	0.0305
HP$	0.0000	0.0005
(CURRHP$)^0.5	-0.0067	0.0000
Out_Wx_Neg	-2.4248	0.0007
Out_Loan_Neg	-2.0500	0.0000
Out_Wx_Pos	3.7320	0.0111
Out_Loan_Pos	2.2771	0.0000

All Outliers, All Obs, Neg Coeffs
Spec #3 (All ARMA, All Vars)

Dependent Variable: ELEC_CONST

Variable	Coeff	Prob.
IND_WX	360.15	0.0017
(INSL$)^0.5	-5.3332	0.0196
LN_LITE$	-80.24	0.0174
Out_Wx_Neg	-2,680	0.0000
Out_Loan_Neg	-1,857	0.0000
Out_Wx_Pos	1,957	0.0000
Out_Loan_Pos	1,328	0.0000

Dependent Variable: ELEC_CDD

Variable	Coeff	Prob.
C	0.4489	0.0028
DW$	-0.0000	0.0557
(FURN$)^0.01	-0.4249	0.0004
(INSL$)^0.01	-0.1884	0.1931
AC$	-0.0002	0.0022
(HP$)^0.01	-0.5646	0.0027
Out_Wx_Neg	-3.9420	0.0000
Out_Loan_Neg	-3.9880	0.0000
Out_Wx_Pos	6.5889	0.0004
Out_Loan_Pos	3.1918	0.0000

Dependent Variable: ELEC_HDD

Variable	Coeff	Prob.
IND_WX	0.1928	0.0836
(INSL$)^0.01	-0.2370	0.0305
HP$	0.0000	0.0005
(CURRHP$)^0.5	-0.0067	0.0000
Out_Wx_Neg	-2.4248	0.0007
Out_Loan_Neg	-2.0500	0.0000
Out_Wx_Pos	3.7320	0.0111
Out_Loan_Pos	2.2771	0.0000

Appendix D

Comparison of All Significant and Only Significant Negative Coefficents Regression Results

All Outliers, All Obs, All Coeffs	All Outliers, All Obs, Neg Coeffs
Spec #3 (All ARMA, All Vars)	Spec #3 (All ARMA, All Vars)

Dependent Variable: NG_CONST (All Coeffs)

Variable	Coeff	Prob.
DW$	-0.0007	0.0001
(INSL$)^0.01	2.7747	0.1260
HWH$	0.0057	0.0854
Out_Wx_Neg	-71.87	0.0000
Out_Loan_Neg	-54.54	0.0000
Out_Wx_Pos	73.49	0.0000
Out_Loan_Pos	71.05	0.0000

Dependent Variable: NG_CONST (Neg Coeffs)

Variable	Coeff	Prob.
DW$	-0.0006	0.0002
HWH$	0.0068	0.0269
Out_Wx_Neg	-68.93	0.0000
Out_Loan_Neg	-54.84	0.0000
Out_Wx_Pos	76.43	0.0000
Out_Loan_Pos	71.01	0.0000

Dependent Variable: NG_HDD (All Coeffs)

Variable	Coeff	Prob.
IND_WX	-0.0288	0.0000
IND_LOAN	-0.0189	0.0000
(DW$)^0.01	0.0192	0.0000
LN_HP$	-0.0014	0.0818
HWH$	-0.0000	0.0219
(INSL$)^0.5	-0.0002	0.0153
Out_Wx_Neg	-0.0829	0.0000
Out_Loan_Neg	-0.1094	0.0000
Out_Wx_Pos	0.0966	0.0000
Out_Loan_Pos	0.2223	0.0000

Dependent Variable: NG_HDD (Neg Coeffs)

Variable	Coeff	Prob.
(FURN$)^0.5	-0.0002	0.0002
(HP$)^0.01	-0.0164	0.0028
HWH$	-0.0000	0.0099
LN_INSL$	-0.0015	0.0004
Out_Wx_Neg	-0.0777	0.0000
Out_Loan_Neg	-0.1191	0.0000
Out_Wx_Pos	0.1019	0.0000
Out_Loan_Pos	0.2213	0.0000