Energy Information at Home:
An Analysis and Policy Projection of the Rebound Effect and U.S. Smart Grid

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Energy Information at Home:
An Analysis and Policy Projection of the Rebound Effect and U.S. Smart Grid

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SUMMARY

This dissertation examines residential energy behavior through three studies. A meta-analysis of the residential rebound effect located 20 studies. Transportation area studies were excluded. A study-level random effects model finds an average rebound effect size of 42%. Fixed effects meta-regression models suggest studies focused on comfort factor, which examines largely consumer behavior change, find 34 – 36 percentage point lower rebound effects than other studies. This difference may be due to issues with predicting savings, implementation, performance, and other factors. Meta-regression findings also suggest rebound effect estimates may be impacted by study characteristics such as the participant selection method, availability of financial incentives, and the measures implemented.

The second study finds current residential smart grid deployment, as determined by Advanced Metering Infrastructure (AMI) installations, correlated with reduced average utility household electricity use. However, the predicted decrease (0.9% reduction at 100% AMI penetration in the residential sector) is lower than some experimental research findings. This suggests current smart grid information feedback may not be fully deployed, optimally designed, or readily accessible.

Lastly, the impacts of national residential smart grid were projected using the National Energy Modeling System. Twelve smart grid scenarios were developed by varying price elasticity and rebound effect in the source code. These scenarios are projected to realize energy and environmental benefits over the long term. However, residential sector energy savings are projected to be greater than all sector savings. With these scenarios for residential smart grid, energy use in the commercial, industrial, and transportation sectors are projected to increase. This suggests cross-sector policies may benefit smart grid implementation.

INTRODUCTION

It may be difficult to imagine how our individual energy patterns impact national energy demand. Many might believe that business and industry have more impact on energy and environment. Perhaps, to the surprise of some, the combined energy decisions of Americans at home exceeds the energy used by the commercial sector in the United States by 3% (U.S. Energy Information Administration, 2015). In 2014, the residential sector consumed about 22% compared to the 19% of total U.S. energy consumed by the commercial sector (U.S. Energy Information Administration, 2015). Further, the residential sector more significantly impacts carbon emissions than the industrial sector. Over a third of national carbon emissions can be attributed to the residential sector, greater than that of the industrial sector, due to its high reliance on electricity (Gardner & Stern, 2008; Vandenbergh, Stern, Gardner, Dietz, & Gilligan, 2010).

Our decisions at home, when examined collectively, have significant national impact. Reductions in residential energy use through energy efficiency or other measures can lead to reductions in carbon emissions and environmental improvement. Energy efficiency is recognized as one of the most productive energy resources (Natural Resources Defense Council, 2013), one that can lead to significant energy savings (Brown, Gumerman, Sun, Baek, Wang, Cortes, & Soumonni, 2010). Household decisions to pursue energy efficiency or changes in energy behavior can, collectively, reduce national energy consumption and improve energy security. How do we realize this potential? Perhaps technology, especially information technology advancements, might empower consumers to capture this potential.

Electricity generation and transmission have long stagnated in terms of innovation. Electrical generation efficiency has not increased for more than half a century while transmission cables are largely 1950s technology facing significant electrical transmission losses (Brown, 2007). Recent energy policy has focused on upgrading current electrical grids. The American Recovery and Reinvestment Act (ARRA) of 2009 provided $4.5 billion in grid modernization support. With a match of over $5.5 billion in private sector funds, grid modernization funds totaled over $10 billion. In June 2011, smart-grid development in rural U.S. received an additional $250 million in loans (U. S. Department of Energy, 2011). Smart grids incorporate information technology within the existing electrical infrastructure, sending information among utilities, power producers, and consumers. Due to improved knowledge and management of electrical system production and demands, smart grids incorporate renewable energy better than the traditional electric grid. Since utility awareness of the electric grid improves with smart grids, issues are fixed more rapidly. Smart grid programs not only provide funds to upgrade and improve the electrical grid, they also support technologies to provide real-time information capabilities within consumers' homes. Smart meters transmit electrical usage to the utility directly without a human meter reader in time intervals of an hour or less. They may also transmit pricing and usage information to the consumer, remotely turn electrical service on or off, and report outage information to the utility (U.S. Department of Energy, n.d.). To date, over 58.5 million smart meters have been installed in the U.S., with about 88% of them in the residential sector (U.S. Energy Information Administration, 2016).

The large financial investments in smart grids were made based on claims that they would advance utility operations, improve customer information and subsequent energy use, and enable a clean energy economy. At the time of the ARRA, "there was very little data from actual smart grid deployments to back up [these] claims" (U.S. Department of Energy, 2011), despite over thirty years of household energy consumption research (e.g., Dubin, Miedema, & Chandran, 1986; Hayes & Cone, 1977; Quigley, 1984; Seligman & Darley, 1977; Shin, 1985; Stern, Dietz, Gardner, Gilligan, & Vandenbergh, 2010). How information, such as real-time energy consumption and pricing information, can be presented to be most useful in consumer energy decisions is a needed area of improvement (Dietz, 2010). Likewise, the translation of behavioral insights into practice has been a missing effort (Allcott & Mullainathan, 2010). Effective use of behavioral insights in technologies like smart meters will help increase residential energy efficiency by providing "credible information at points of decision" (Vandenbergh et al., 2010). These areas of knowledge are key to understanding the impact of smart grid technologies and how they can be best utilized.

Smart grid projects can help realize the potential of information programs in altering consumer behavior. The acknowledgement of how additional information impacts human decision making goes against traditional economic assumptions. In reality, consumers generally tend to underestimate their energy use and savings (Attari, DeKay, Davidson, & De Bruin, 2010). Residential consumers have minimal knowledge of energy units, consumption, and other related knowledge (Attari, DeKay, Davidson, & de Bruin, 2011; Carrico et al., 2010; Frederick, Meyer, & Mochon, 2011). In general, the U.S. population has low environmental literacy, to which energy knowledge is greatly linked, likely due to fragmented environmental exposure provided by media sound bites (McKeown, 2007). Smart grid technologies provide a platform to improve consumer energy and environmental knowledge. Leveraged effectively, they may significantly alter U.S. residential energy demand by providing easily accessible information, improving consumer knowledge, and informing behavioral change.

Energy savings from household behavioral changes can result in up to 20% reduction in residential emissions (Dietz, Gardner, Gilligan, Stern, & Vandenbergh, 2009). Since "energy use is not a behavior but an outcome of behavior" (Stern, 1992), policies expecting to affect residential energy use require a realistic behavioral model to realize policy goals. In reality, the "self-focused maximization of consequential material outcomes" is only a subset of goals driving human behavior (Weber & Johnson, 2012). Actual human behavior is complex and impacted by various factors.

How people behave impact the success of energy programs and policies. The Hood River Conservation Project achieved a high participation rate of 85% of eligible households in retrofit measures in part due to the mobilization of social networks through word-of-mouth recruitment (Hirst, 1989). Households with similar equipment and device setups exhibited an almost 40% difference in actual energy use, one attributed to differences in behavior (Desmedt, Vekemans, & Maes, 2009).

Even in the same household, different behavior can occur. When a household purchases an energy efficient technology, their energy behavior may change. This phenomenon is called the rebound effect or the takeback effect (e.g., Deurinck, Saelens, & Roels, 2012; Dinan & Trumble, 1989; Schwarz & Taylor, 1995). After consumers implement an energy efficient technology, energy savings are predicted by assuming the same energy behavior before efficiency implementation. The rebound effect occurs when the predicted energy savings are not realized fully. Consumers "take back" some of the potential energy savings from the efficient technology when they use more energy services after efficiency implementation. Energy efficient technologies effectively reduce the unit price of the provided energy service. Householders may opt to use the energy service provided by efficient technology more.

Householders may also opt to use other energy services more as they apply the monetary savings from efficiency implementation elsewhere (Greening, Greene, & Difiglio, 2000).

Policies designed with a false or incomplete understanding of human behavior may fail to realize the projected technical energy efficiency potential. Policies aimed towards reduction in residential sector energy use should intervene at the level of the decision maker, the residential consumer (Dietz, Stern, & Weber, 2013). A better understanding of how consumers respond to new technologies may lead to better predictions of energy policy impacts. With an improved understanding of decision factors impacting household energy use, policymakers may craft more effective residential policies.

In recent years, the number of studies regarding consumer behavior, especially addressing novel energy technologies and rapid real-time provision of energy information, has increased. Many researchers promote more multi-faceted and comprehensive approaches in examining consumer behavior and how it relates to energy use (e.g., Gram-Hanssen, 2010; Van den Bergh, 2008). Though these efforts arise from varied disciplinary areas, they all recognize the complexity of human behavior, a complexity that cannot be explained fully by existing theories. These efforts also recognize the impact of individual, social, and cultural variables. As the understanding of human behavior improves, it has been readily incorporated into energy use models, blending social, psychological, and economic approaches (e.g., Czap & Czap, 2010; Hargreaves, Nye, & Burgess, 2013; Hori, Kondo, Nogata, & Ben, 2013; Sahakian & Steinberger, 2011; Sardianou, 2007; Thogersen & Gronhoj, 2010; Urban & Scasny, 2012).

The work reported here examines the impact of information, like that provided by smart grid technologies, on consumer behavior and energy use. This study uses a comprehensive approach to understand residential consumer energy behavior through three analytical chapters.

The first analytical chapter, a meta-analysis of residential rebound effect, examines how consumers respond to energy efficiency measures. A meta-analysis is well suited for examining the current state of a field, especially where small sized studies, like some rebound effect studies, dominate (Card, 2012). No meta-analysis of this subject area has been yet conducted, despite the vitriolic arguments over the magnitude of the rebound effect. One faction believes the rebound effect to be smaller than the overall energy savings (<100%) and the other faction believes it is larger than the overall energy savings (>100%), thereby leading to an increase in energy use with energy efficiency implementation (González, 2010).

Next, an analysis of advanced metering infrastructure projects, a key component to smart grid, determines how current smart grid developments have impacted residential energy consumption. A more integrative approach is taken, one that includes consumer socioeconomic variables and socio-physical characteristics.

Lastly, the results from the previous analyses inform inputs in the National Energy Modeling System to forecast a national residential smart grid. This allows examination of residential smart grid policies with more realistic rebound effect assumptions on regional and national energy demand over the long term. Sensitivities with different rebound effect and price elasticity of electricity assumptions are performed to determine the impact of varied consumer behaviors and assumptions.

Overall, this project increases the understanding of factors affecting energy behavior and demand and how these impact future policy projections. This work contributes to the accumulating research on consumer energy behavior. Currently, policy makers and utility operators need more understanding of actual consumer behavior to design effective programs. It is imperative that the impact of smart grid technology and energy efficiency measures be well understood to craft pertinent and successful energy policies.

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CHAPTER 2. META-ANALYSIS OF RESIDENTIAL REBOUND EFFECT

2.1 Introduction

Energy efficiency is often cited as an effective measure to help combat climate change through its reductions in energy use and associated emissions. In the residential sector alone, the combination of energy efficiency measures and behavioral changes has been projected to reduce 20% of direct household emissions and over 7% of total U.S. national emissions (Dietz, Gardner, Gilligan, Stern, & Vandenbergh, 2009). However, the issue of the rebound effect, the re-optimization of demand given the price and income changes from energy efficiency implementation (Borenstein, 2015), continues to be a thorn in the side of energy efficiency advocates. The rebound effect issue has led to statements such as (Herring, 2006):

> *…energy efficiency is not as 'environmentally friendly' as many claim. Its promotion will not necessarily lead to a reduction in energy use and hence reduced CO_2 emissions.*

The rebound effect leads to uncomfortable implications for energy and climate policy. This discomfort may lead many researchers to ignore the rebound effect issue, despite its policy and environmental significance (Sorrell, 2009). The size of the rebound effect, which dictates whether energy efficiency does or does not realize energy and environmental benefits, remains contentious (Freire González, 2010). Conversations about the impacts of energy efficiency and the rebound effect are inconclusive, polarized, and many times theoretical (Sorrell, 2009). However, these previously academic disagreements have spilled into the mainstream press (Herring, 2006), with recent publications in *The New York Times* and *The New Yorker* (Owen, 2010; Revkin, 2014a, 2014b; Shellenberger & Nordhaus, 2014; Tierney, 2011). The controversy regarding the size and source of the rebound effect needs to be addressed to create effective policies (Greening, Greene, & Difiglio, 2000).

The rebound effect describes the phenomenon where energy efficiency implementation saves less energy than expected (e.g., Deurinck, Saelens, & Roels, 2012; Dinan & Trumble, 1989; Schwarz & Taylor, 1995). It is usually attributed to change in consumer energy behavior after efficiency implementation. Inconsistent usages and definitions of rebound effect add to the contention and confusion (Borenstein, 2015; Greening et al., 2000). The term rebound effect arose from the microeconomic literature to describe how technical efficiency improvements can increase the supply of an energy service and its demand (Khazzoom, 1980, 1987, 1989). Since then, rebound effect has also been used to describe macroeconomic effects (Greening et al., 2000).

The rebound effect literature is dominated by a dichotomy of usually small experimental direct measure studies and large econometric studies. Direct measure studies many times have poor methodological quality, lacking random assignment of experimental households, control groups, and large study sizes (Greening et al., 2000; Sorrell, Dimitropoulos, & Sommerville, 2009). These studies do not have the rigorous design of true experiments and are called quasi-experimental studies. Quasi-experimental studies are often dismissed due to small sample sizes and potential complications. Researchers, like Greening et al., often emphasize econometric findings over direct measure ones (2000). Yet, quasi-experimental studies are the only ones that examine consumer behavior in-place and try to measure its impact on energy use.

The dismissal of quasi-experimental studies for their shortcomings effectively minimizes or removes the contributions of engineering and consumer behavior studies from the rebound effect conversation. To craft effective policies and to improve efficiency equipment, a thorough understanding of real world consumer energy behavior is required. Stern notes the integration of knowledge across fields is necessary to understand individual household interactions with energy systems and that the knowledge of one discipline rarely provides enough insight to fully grasp such interactions (2014). The dismissal of the quasi-experimental literature is a loss of information to consider and guide future energy research.

Research at the micro level, focusing on an individual household or small samples, can provide unique insights into consumer behavior. As Bladh (2011, p. 238) says, “the advantage of micro-level studies is that you can find the mechanisms at work in a process of change” and examine the “fine details of consumer behavior.” Many econometric studies rely on historical or cross-sectional energy price variation to estimate rebound effect from price elasticity. These studies are not immune to bias and may provide over-estimates of rebound effect (Sorrell & Dimitropoulos, 2008; Sorrell et al., 2009). They also miss household level interactions that quasi-experimental studies can capture. This study aims to address the current emphasis on econometric findings within the rebound effect literature by examining the quasi-experimental residential literature and its contributions.

Meta-analysis is a statistical tool that allows researchers to assess the current state of a field through including all relevant studies, regardless of sample size (Card, 2012). No meta-analysis of the quasi-experimental residential rebound effect studies has been yet conducted, despite the vitriolic arguments over the rebound effect magnitude. This chapter examines the rebound effect through a meta-analysis of the quasi-experimental residential energy efficiency literature. This analysis aims to clarify what the quasi-experimental research says about the rebound effect and its size. First, pertinent literature is covered, followed by research goals, data description, and methodology. Results, discussion, and conclusions follow.

2.2 Literature Review

2.2.1 Rebound Effect Components and Size

Energy efficiency saves money by using less energy to provide the same level of service as a less efficient measure. The rebound effect is the re-optimization of demand based on price and income changes caused by energy efficiency implementation (Borenstein, 2015). The microeconomic view of rebound effect divides it into two effects, direct and indirect rebound. The direct rebound effect occurs when the monetary savings from efficiency are spent on using the energy efficient service more. This can be decomposed into income and substitution effects in consuming the energy service in question (Berkhout, Muskens, & Velthuijsen, 2000; Borenstein, 2015; Greening, Greene, & Difiglio, 2000). The indirect rebound effect occurs when monetary savings from energy efficiency are applied to other areas of consumption. Though this is an income effect, it is not the full income effect from energy efficiency upgrade which also includes the consumption change of the efficient energy service due to income effect (Borenstein, 2015). If energy cost is low, actual household income savings from efficiency is small. The indirect residential rebound effect is likely small (Greening et al., 2000).

There are many empirical estimates of rebound effect. After reviewing the direct rebound effect literature, Sorrel finds a residential rebound effect of generally less than 30% (Sorrell, Dimitropoulos, & Sommerville, 2009). Greening et al. review 75 empirical studies of rebound effect. From this, they estimate a 10-30% rebound effect for space heating, 0-50% rebound effect for space cooling, and 5-20% rebound effect for lighting (Greening et al., 2000). Borenstein finds rebound effects reduce energy savings by 10-40% (2015). Sanders and Phillipson examine 13 papers on insulation retrofits in UK households. They find a rebound effect of 50%, of which 15% is attributed to the comfort factor (Sanders & Phillipson, 2006).

The rebound effect can lead to economy-wide and transformational changes. The economy-wide rebound effect is the totality of direct and indirect rebound effects from energy efficiency implementation (Sorrell, 2009). Economy-wide impacts, in turn, may lead to transformational changes. As consumer preferences change, technologies adjust, and social institutions and norms revise, society itself may transform (Greening et al., 2000). Sometimes, the rebound effect is estimated to be over 100% of the expected savings. This special case is called "backfire," where the increase in energy use exceeds theoretical savings from the efficiency measure (Jenkins, Nordhaus, & Shellenberger, 2011; Sorrell, 2009). See Figure 1 for a summary diagram of the rebound effect, its estimated size, and terminology.

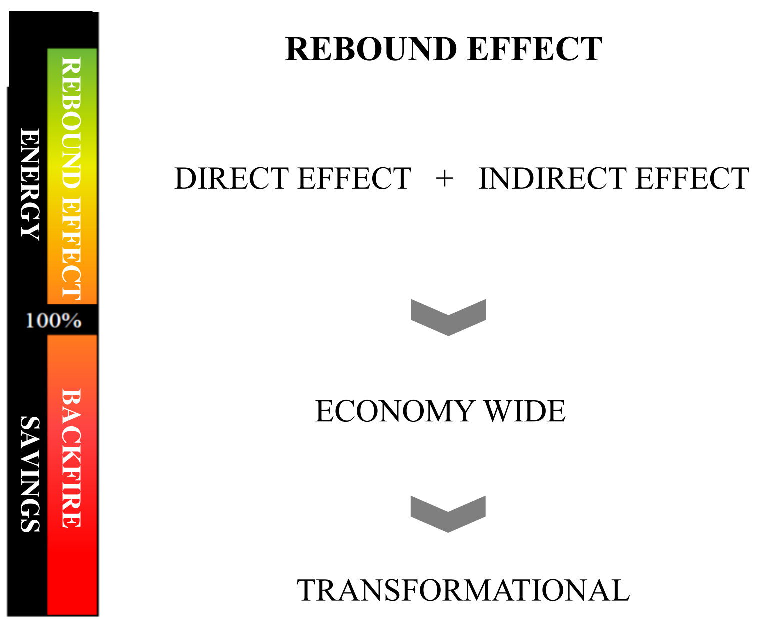

Figure 2-1. **Summary of Rebound Effect**

Research supporting backfire focus mainly on the macroeconomic impacts and are largely theoretical (Sorrell, 2009). The idea of backfire is not new. The Jevon's Paradox, first introduced by William Stanley Jevons in 1895, is widely cited in the reformulated Khazzoom-

Brookes Postulate (Sorrell, 2009), which states "With fixed real energy price, energy efficiency gains will increase energy consumption above where it would be without these gains" (Saunders, 1992). Estimating the macroeconomic effect of many microeconomic changes in energy use is impossible, causing a lack of strong empirical support for backfire (Brookes, 2000). Historical evidence frequently is cited, where energy efficiency innovations led to greater energy demand by enabling other processes or products (Sorrell, 2009). For instance, energy efficient innovations in steel production allowed new applications for steel that led to greater overall energy use (Rosenberg, 1989).

The difficulty of separating energy efficiency improvements from other attributes of an energy service complicates the issue. Energy services are provided by a combination of useful work and broader attributes (Sorrell & Dimitropoulos, 2008). Demand for an energy service may increase due to demand for other attributes and changing societal interest. To attribute increased demand to only the efficiency improvement and the rebound effect would be incorrect (Borenstein, 2015; Sorrell, 2009).

Rebound effects can be estimated in varied ways for varied system boundaries, but there is no consensus as to which system boundary should be used (Sorrell, 2009). Rebound effect can be calculated at varied system levels such as household, sector, or economy wide. The lack of a consensus system boundary for rebound estimations may also contribute to the disagreement on the size of the rebound effect and the impacts of energy efficiency.

2.2.2 Rebound Effect and Quasi-Experimental Research

Quasi-experimental research pertaining to residential rebound effect measure the impacts of household energy efficiency retrofits. Conducting household level research requires access to homes for data collection and instrumentation, which can be difficult to obtain. Sample sizes are many times small, varying from a single household to a few thousand. Very rarely do studies on energy efficiency and rebound effect have sample sizes of millions or more. Studies on an individual home are more likely to provide detailed consumer behavioral information from interviews. For instance, Meier and Nordman provide detailed information regarding five households, with information to calculate rebound effect for each. With a small number of homes, they detail the specifics of each house, such as size, supplemental heating, and insulation levels. The researchers can then better explain why certain households saved more or less energy than expected (Meier, Nordman, Miller, & Hadley, 1989). Bladh also conducts lighting retrofits in a single home, converting nearly all lights to LED and CFLs. From the homeowner interview, Bladh knows a period of low energy use was due to absence from the home. The homeowners describe their views on individual lights, from the color, brightness, and compatibility with existing fixtures (Bladh, 2011). Details on household behavior and attitudes toward energy efficient retrofits allow a better understanding of the rebound effect size.

Terminology for the rebound effect can be confusing. Outside of rebound effect, other terms like take-back effect, reduction factor, comfort factor, shortfall, and snap-back are also used (Sanders & Phillipson, 2006; Scheer, Clancy, & Hogain, 2013; Sebold & Fox, 1985). Though these terms are used interchangeably at times, they are not necessarily equivalent. The "take-back effect" reflects the idea that consumers "take back" some portion of the energy savings.

Similarly, "comfort factor" reflects how some consumers increase comfort, especially by increasing indoor temperatures, after efficiency implementation. Comfort factor is the energy increase due to improved internal temperature, but it is sometimes confused with the rebound effect or reduction factor (Sanders & Phillipson, 2006).

The rebound effect is mathematically expressed as the percentage difference in actual and calculated energy consumption after energy efficiency implementation (See Equation 1) (Druckman, Chitnis, Sorrell, & Jackson, 2011; Freire-González, 2011; Haas & Biermayr, 2000).

$$Rebound\ Effect = \frac{Calculated\ Savings\ - Actual\ Savings}{Calculated\ Savings}$$

Theoretically, the rebound effect as calculated by Equation 1 should be attributed to only consumer behavior change and equivalent to the take-back effect and comfort factor. Many times, it is taken to be equivalent, as in the case of the most energy efficiency programs in the UK (Henderson, Staniaszek, Anderson, & Philipson, 2003). In application, however, other issues unrelated to actual consumer behavioral change can increase the difference between theoretical and actual energy savings.

Several issues can inflate the estimated rebound effect that are unrelated to consumer behavioral change. If the theoretical savings are calculated from inadequate models, the predicted savings will be flawed (Sanders & Phillipson, 2006; Sorrell, Dimitropoulos, & Sommerville, 2009). If inaccurate engineering models predict more savings than actually possible, the rebound effect will be inflated. Improper installation might decrease measured effectiveness and the realized energy savings (Sorrell et al., 2009). For instance, existing homes may lack insulation in some wall areas. Installers may not detect that and believe the home is fully insulated when it is not (Hong, Oreszczyn, & Ridley, 2006). Defective manufacturing or unforeseen issues might lead to measures performing below advertised levels, leading to larger rebound effects (Sorrell et al., 2009). Inadequate recruitment of the target population may also decrease a program's expected savings by inflating the theoretical savings. In Mexico's appliance replacement program, households with older appliances are not well represented. Only 5% of air conditioners were a more than 15 years old and only 10% of refrigerators were 20 years or older. This low recruitment of the target population may contribute to the low realized energy savings (Davis, Fuchs, & Gertler, 2014). These inflating issues arise due to complications in estimating energy savings and implementing energy efficiency measures. None of these issues are from consumer behavior change after energy efficiency implementation.

Due to these issues which act to artificially inflate the rebound effect, calculation of the rebound effect using the rebound effect equation will usually generate an overestimate of the rebound effect when applied to empirical results. See Figure 2-2 for a diagram of possible complications that enlarge the difference between theoretical and actual energy savings.

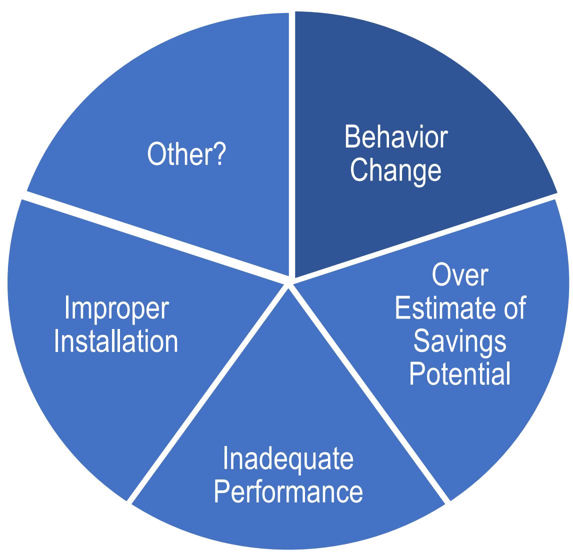

Figure 2-2. Causes of Energy Savings Shortfall in Empirical Studies

There are also cases where actual energy savings exceed theoretical predictions. Weatherization and insulation might lead to improved thermal comfort by reducing drafts. In these cases, homeowners might feel just as warm at a lower thermostat setting than before implementing the efficiency measures. If the theoretical calculations of energy savings did not consider savings from improved thermal comfort, then more energy might be saved than predicted, leading to a negative rebound effect.

Efforts to increase the accuracy in which rebound effect is calculated from empirical research have been limited. Most efforts center on improving the engineering models that estimate theoretical energy savings from energy efficient upgrades. Few, if any, other efforts have been made to understand other aspects inflating rebound effects. This, in part, may be due to the dismissal of quasi-experimental research in the rebound effect literature. More work to examine household energy behavior is required.

2.2.3 Introduction to Meta-Analysis

Meta-analysis is a methodological and statistical review summarizing past empirical research addressing similar or identical hypotheses (Card, 2012; Cooper, 2010; Lipsey & Wilson, 2001; Nelson & Kennedy, 2009). It can alleviate the difficulty of comparing and contrasting findings from different studies (Card, 2013). The process reveals the state of knowledge in a study area and elucidates areas of future research (Cooper, 2010). Meta-analysis has been used broadly in the health sciences, psychology, education, marketing, and the social sciences (Nelson & Kennedy, 2009). It now encompasses all methods and techniques of quantitative research synthesis (Lipsey & Wilson, 2001).

Meta-analyses do not deal with raw data specifically since they analyze the results of multiple studies. A common empirical value is examined from a set of studies. This common value is called the effect size. The studies inform a combined estimate of effect-size and may help explain study-to-study variation (Nelson & Kennedy, 2009). By examining bodies of literature, meta-analyses allow scholars to understand how individual variables impact effect size. These variables may be sample characteristics such as socioeconomic data, study size and location, and other independent variables (Card, 2012).

A meta-analysis can include studies of any size, regardless of the statistical significance of the individual findings. The focus in a meta-analysis is on the effect size, not the significance, from each study. In this way, meta-analysis is a preferred tool for examining research areas with small studies, which individually provide inconclusive evidence (Card, 2012).

2.3 Research Goal and Hypotheses

In this meta-analysis, the research goal is to examine the typical residential rebound effect in quasi-experimental research where efficiency measures are implemented. This study seeks to distill lessons from these energy efficiency studies and their rebound effect implications. Though there are vocal supporters of large rebound effects and potentially backfire, much of the literature supports moderate rebound effects. I hypothesized that the residential rebound effect exists (i.e., is greater than zero), but it is less than the possible energy savings from efficiency (i.e. is less than 100%).

2.4 Data Sources

The following areas were searched for relevant studies:

- published peer-reviewed literature,
- published non-peer reviewed literature,
- utility studies on rebound effect,
- utility studies on energy efficiency,
- conference proceedings,
- white papers,
- and unpublished literature.

Academic databases were used to gather pertinent rebound effect studies from the published literature. Example academic databases are: Academic Search Complete, EconLit, JSTOR, Web of Knowledge, and Google Scholar. Non-academic literature was located using search engines.

2.5 Methodology

2.5.1. Effect Size and Unit of Analysis

Residential rebound effect estimates are from the literature directly, if estimates were consistent with Equation 1, or calculated using provided information. The rebound effect is used in its raw form due to the clarity of its interpretation and the avoidance of complications introduced by standard-deviation scaling (Bond, Wiitala, & Richard, 2003). The unit of analysis is each individual estimate of residential rebound effect.

2.5.2 Literature Search and Inclusion Criteria

Empirical studies pertaining to the residential rebound effect and energy efficiency were located using academic literature and internet searches. Only studies pertaining to the residential sector were included. Studies focusing on residential transportation were excluded. Studies were included if they pertained to the:

- residential sector,
- rebound effect for all utilities (electricity, natural gas, and water),
- energy efficiency studies with information to calculate the rebound effect,
- and studies reporting the rebound effect from efficiency implementation.

Of the 231 located studies, 19 studies met these criteria. Most of these studies (16) were from the published academic literature. There was one conference paper, academic white paper, and government report. In some cases, such as Roy's study on solar lighting in India (2000), additional literature was required to complete coding (Roy & Jana, 1998). One study, by Scheer, was cited in a published article even though the data are from a dissertation (Haas & Biermayr, 2000; Scheer, 1996). Through communications with authors regarding additional information, a twentieth study was recommended. This study on appliance replacement in Mexico was published in late 2014 (Davis et al., 2014). See Appendix A.1 for documentation of the literature search. See Appendix A.3 for the final list of located rebound effect studies.

2.5.3 Data Coding

Publication details were coded to allow analysis of publication bias. These include venue of publication, year of publication, and author affiliation. Study details such as sample size, sample collection method, and duration of study, were also included. Likewise, household socioeconomics and the implemented efficiency measures were also included. For empirical publications, papers that mention possible complications impacting the rebound effect, such as issues with theoretical calculations of savings and improper installation, were also be noted. In cases where additional information was required to calculate standard deviation, authors were contacted, if possible, to request further information. See Appendix A.2 for the coding protocol.

2.5.4 Statistical Analysis

Two models are commonly used in meta-analyses, the fixed effects and random effects models. The two models differ conceptually in their estimation of the effect size. The fixed effect model assumes there is one population effect size and any differences from this are due to sampling error. The random effects model assumes a distribution of population effect sizes, (Borenstein, Hedges, Higgins, & Rothstein, 2009; Card, 2012; Cooper, Hedges, & Valentine, 2009). Both the fixed effects and random effects models were examined for this analysis.

Some of the examined studies did not provide sufficient statistical information to calculate standard deviations directly. Several estimates of rebound effect were also from a single individual household or multi-family building and not from a sample population.

Usually, each study in a meta-analysis has a weight that is proportional to the inverse conditional variance. Though formulas for the conditional variance differ depending on the effect size indices, they are all inversely proportion to the sample size of each study. In this way, larger studies have more weight within the meta-analysis than smaller studies (Konstantopoulos & Hedges, 2009). Due to incomplete information, the usual methods of weighting effect sizes could not be pursued for all studies in this analysis.

Two methods of weighting were used. Due to missing statistical information for some studies, especially ones with only a sample size of one, the first method weighted studies by sample size in a fixed effects model. The second method, used to generate a random effects model, weighted effect size by standard meta-analysis procedures of inverse conditional variance. Since not all effect size estimates have standard deviations associated with them, the number of rebound effect estimates decreases. Averages and standard deviations were calculated for some studies that provided several estimates of rebound effect from individual households. The twenty studies provided 162 estimates of rebound effect. Only 81 estimates of rebound effect provided information to calculate or estimate standard deviation. If the outlier study is removed, only 62 estimates of rebound effect have standard deviation information. In some cases, standard deviation could be estimated from provided information. In the cases where the standard deviation is provided for the average savings, the standard deviation for the rebound effect can be calculated by the following formula:

$$s_{RE} = \frac{s_{AS}}{C}$$

where s_{RE} is the sample standard deviation of the rebound effect, s_{AS} is the sample standard deviation of the average savings, and C is the calculated or theoretical savings. See Appendix B for the derivation of this formula.

In cases where only the range of values was provided, the standard deviation was estimated from the range using the following formulas suggested by Hozo, Djulbegovic, and Hozo (2005):

$$s \approx \sqrt{\frac{1}{12}\left(\frac{(a-2m+b)^2}{4} + (b-a)^2\right)} \qquad \text{for N} \leq 15$$

$$s \approx \frac{b-a}{4} = \frac{R}{4} \qquad \text{for N} > 15$$

where *s* is the sample standard deviation, *m* is the median, *a* is the low end of the range, *b* is the high end of the range, R is the range, and N is the sample size. Estimating the standard deviation by R/4 was used rarely and only if no other methods were available.

For small sample sizes, the median was estimated using the following formula for mean (Hozo, Djulbegovic, & Hozo, 2005).

$$\bar{x} \approx \frac{a+2m+b}{4} + \frac{a-2m+b}{4N}$$

Solving for the median, m, we get:

$$m \approx \frac{\bar{x} * 4N - a(N+1) - b(N+1)}{2(N-1)}$$

Some statistical options for meta-analyses only examine study-level data, such as *metareg* and *metaan* commands in Stata. Therefore, weighted averages were obtained for each study to generate one estimate of rebound effect for each study. The estimates for rebound effect were weighted by the study size for each estimate, which sometimes varies within studies for different rebound effect estimates. In the case where study size did not vary or was not reported to vary, the effect estimates were weighted equally.

Fixed effects models were generated using the *metaan* and *areg* commands in Stata. Random effects models were examined using *metareg* command, which allows a meta-analysis regression or meta-regression, and *metaan* command, which requires only the effect size and standard errors (Harbord & Higgins, 2008; Kontopantelis & Reeves, 2010). In the case for both *metareg* and *metaan*, study standard errors are substituted by the inverse study size. This weights the analysis by study size, allowing larger studies to hold more weight in the results.

2.6 Summary of Collected Studies

There is significant variation in study characteristics, end uses of efficiency measures, and reporting in the targeted research. Sometimes, the mean rebound effect was given or enough information was provided to calculate it. Other times, this information was missing and the study had to be excluded. Even in cases where the rebound effect is given or can be calculated, sometimes no deviations or confidence intervals were provided. In these cases, the authors were contacted, if possible, to request the missing information.

Twenty studies were collected, providing 162 estimates of rebound effect. Of these studies, one far surpassed the others in study size (Davis et al., 2014). It has sample sizes of up to 1.9 million households, while other studies had more modest sample sizes ranging from one to 7,923 households. This outlier study was excluded in some of the analyses for comparison purposes. This study does not itself predict the energy savings from appliance replacement. Instead, it compares actual savings to assumed savings from a World Bank report (Davis et al., 2014). The World Bank report does not detail how it arrived at its assumptions for air conditioner and refrigerator replacement (Johnson, Alatorre, Romo, & Liu, 2010). Davis et al. discuss the World Bank estimates for refrigerators and air conditioner replacement savings and find that it likely assumes mainly older appliance replacements. In the Davis report, only 10% of refrigerators were 20 years or older and only 5% of air conditioners were 15 years or older (Davis et al., 2014). This discrepancy may cause the predicted energy savings to be unrealistically high for the appliance replacements in the Davis study, thereby artificially inflating the calculated rebound effect. The 19 remaining studies provide 142 rebound effect estimates. Table 2-1 details the authors, year of publication, publication type, country, and study size.

Table 2-1. Publication Type, Nation, and Study Size from Collected Studies

	Authors	Year	Publication Type	Country	Study Size (min/max)
1	Bell and Lowe	2000	Journal	UK	(1/30)
2	Bennear et al.	2013	Journal	US	683
3	Bladh	2011	Journal	Sweden	1
4	Davis	2009	Journal	US	95
5	Davis et al.	2014	Journal	Mexico	(957,080/1,914,160)
6	Elmroth et al.	1984	Journal	Sweden	(10/51)
7	Gram-Hanssen et al.	2012	Journal	Denmark	(42/70)
8	Scheer	1996	Dissertation	Austria	(1/11)
9	Henderson et al.	2003	Conference	UK	(28/7,923)
10	Hewett et al.	1986	Journal	US	(1/20)
11	Hirst et al.	1985	Journal	US	(1/243)
12	Hirst	1986	Journal	US	(1/484)
13	Hirst et al	1989	Journal	US	2362
14	Hong et al.	2006	Journal	UK	(22/720)
15	Martin and Watson	2006	Report	UK	59
16	Meier et al.	1989	Journal	US	1
17	Roy	2000	Journal	India	38
18	Sanders and Phillipson	2006	Report	US	(59/1,632)
19	Scheer et al.	2013	Journal	Ireland	210
20	Sebold and Fox	1985	Journal	US	450

Table 2-2 details the number of estimates from each study and the minimum, maximum, and median effect sizes. It also provides a weighted average for the rebound effect size for each study. The average is weighted by the sample size used to generate each rebound effect estimate, which can vary from estimate to estimate within each study. For studies where no variation in sample population was provided for each rebound effect estimate, each estimate was weighted equally.

Table 2-2. Summary of Rebound Effect Estimates from Collected Studies

Authors		Year	Rebound Effect				
			Estimates, Number	Min	Max	Median	Average, Weighted*
1	Bell and Lowe	2000	3	0.29	0.66	0.38	0.63
2	Bennear et al.	2013	3	0.01	0.19	0.18	0.12
3	Bladh	2011	1	-0.69	-0.69	-0.69	-0.69
4	Davis	2009	3	-0.01	0.08	0.01	0.03
5	Davis et al.	2014	21	0.69	1.09	1.03	0.91
6	Elmroth et al.	1984	27	-2.13	0.63	0.05	-0.21
7	Gram-Hanssen et al.	2012	3	0.19	1.00	0.20	0.41
8	Scheer	1996	12	-0.02	0.61	0.29	0.30
9	Henderson et al.	2003	30	-2.11	0.97	0.65	0.67
10	Hewett et al.	1986	6	0.21	0.55	0.36	0.31
11	Hirst et al.	1985	9	-0.10	2.30	0.34	0.54
12	Hirst	1986	4	0.20	0.55	0.38	0.38
13	Hirst et al	1989	2	0.20	0.57	0.39	0.39
14	Hong et al.	2006	6	0.06	1.00	0.87	0.61
15	Martin and Watson	2006	3	0.16	0.40	0.29	0.28
16	Meier et al.	1989	10	-0.69	0.91	0.00	0.10
17	Roy	2000	3	0.50	2.00	0.80	1.10
18	Sanders and Phillipson	2006	6	0.14	0.53	0.29	0.63
19	Scheer et al.	2013	1	0.36	0.36	0.36	0.36
20	Sebold and Fox	1985	10	0.19	0.86	0.63	0.62

*The average is weighted by the effect size sample size, which can vary within each study by estimate.

2.7 Results and Discussion

Ideally, the random effects model should be used for meta-analyses of studies with different study designs, as it is unlikely that there is one true population effect size across studies with different designs and sample populations (Borenstein, Hedges, & Rothstein, 2007;

Konstantopoulos & Hedges, 2009). In small sample meta-analyses, the fixed effects model can be used when the random effects model cannot be estimated (Borenstein et al., 2007; Konstantopoulos & Hedges, 2009). This study explores random effects and fixed effects models for the rebound effect meta-analysis using study level data and effect size level data. In cases where the random effects model cannot be estimated, the study examines fixed effects models.

2.7.1 Study Level Results

The *metaan* command was used to generate the fixed effects and random effects models using study level data, where each study provides one estimate for rebound effect. Four different methods for random-effects models were used: the DerSimonian-Laird, maximum likelihood, restricted maximum likelihood, and profile likelihood methods.

All random effects models generated an overall rebound effect estimate of 0.42 or 42%. Only the random effects model for the most commonly used method, the DerSimonian-Laird method (Kontopantelis & Reeves, 2010), is reported. See Figure 2-3 for the forest plot for this random-effects model. The forest plot provides each study's weight, which is based on study size where larger studies have more weight. The effect sizes (ES) presented are the weighted averages of rebound effect estimates within each paper. The 95% CI are also provided, but should be considered cautiously as they are estimated based on inverse sample size and not actual standard errors, which were not available for all studies.

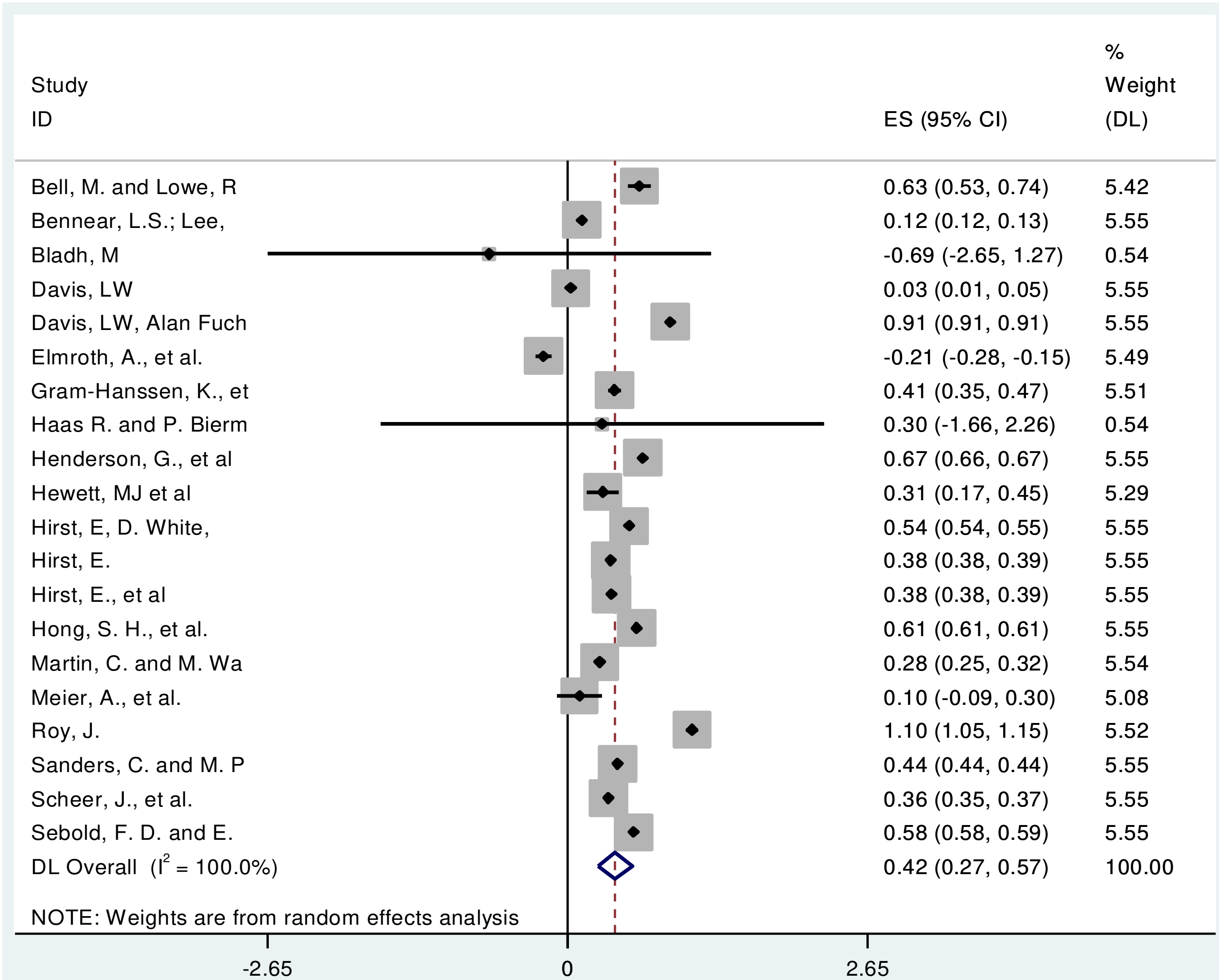

Figure 2-3. Random-Effects Model Forest Plot (DerSimonian-Laird Method)

The overall estimated rebound effect is 0.42 and the 95% confidence interval does not include zero, suggesting the overall effect size is significant at the 95% level. As this is a random effects model, this overall estimated rebound effect is the estimated mean of rebound effect estimates. According to the heterogeneity measures such as I^2, there is considerable heterogeneity across studies. This suggests that the rebound effect literature in this sample, though quite disparate, appears to have an average rebound effect of around 42%. This study does not support claims of backfire and finds the average rebound effect to be less than 100%.

Even though consumers increase their energy use after energy efficiency implementation, an average of 58% of the expected energy savings from efficiency are retained.

The fixed effects model is not preferred due to its assumptions of one true mean. In the fixed effects model, the overall effect size is 0.88 (See Appendix C for the fixed effects model forest plot). Large studies are given more weight in fixed effects models and the result is based on two large studies, with all other studies given zero weight. Since the rebound effect literature examines different populations, applications, and study designs, it is unlikely that there is one true rebound effect estimate. Because of this, the random-effects model is preferred in the examination of study-level data.

2.7.2 Estimate Level Results

Further analyses were conducted at the effect estimate level. Instead of confining the analysis to study level estimates, where each of the twenty studies provide one estimate, like in the previous analysis, the following analyses use all or nearly all estimates of the rebound effect. This expands the data analyzed from twenty to up to 162 estimates of rebound effect.

The random effects model was implemented using the *metareg* command in Stata. Two versions were attempted. The first one used the data subset with reported, calculated, or estimated standard errors and these were used to weight the data. The second one used the inverse study size to weight estimates by sample size. No predictors were significant in either random effects meta-regression likely due to the low number of studies in this meta-analysis which make it difficult to measure variation between studies with precision (Borenstein et al., 2007; Konstantopoulos & Hedges, 2009).

In small sample meta-analyses, the fixed effects model can be used (Borenstein et al., 2007; Konstantopoulos & Hedges, 2009). In this case, only the fixed effects models provided any significant predictors. The FE model of the rebound effect meta-analysis was conducted using the *areg* command in Stata. Estimates were weighted by sample size.

2.7.2-1 Impact of Individual Study Variation

Two FE models examining within study impacts are shown in Table 2-3. The first model does not include the outlier study by Davis et al. with much larger study sizes than the other studies within the meta-analysis. The second model excludes the outlier study.

Table 2-3. Fixed Effects Models Within Study

	VARIABLES	**(1) Without Outlier Study**	**(2) With Outlier Study**
	Study Size	-8.63E-07	1.18e-08*
		(1.51E-05)	(6.73E-09)
	Single Family House	0.112	0.102
		(0.117)	(0.309)
	Preferred Estimate	0.0323	-0.000464
		(0.0920)	(0.00644)
	Comfort Factor	-0.359***	-0.359
		(0.114)	(0.304)
	Heating and Cooling	0.533***	0.334***
		(0.144)	(0.00393)
	Water Heating	0.412***	0.323
		(0.155)	(0.377)
Efficiency Measures	Insulation	0.046	0.0405
		(0.191)	(0.510)
	Weatherization	-0.221	-0.212
		(0.216)	(0.576)
	Windows/Doors	0.318	0.316
		(0.215)	(0.573)
	Programmable Thermostat	0.227	0.251
		(0.336)	(0.896)
	Lighting	-0.342	-0.276
		(0.382)	(1.014)
	Other Measure	0.587***	0.493
		(0.192)	(0.480)
	Constant	0.369**	0.708***
		(0.184)	(0.0124)
	Observations	141	162
	R-squared	0.499	0.982

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The rebound effect estimates vary depending on the implemented efficiency measures. FE (1), which excludes the outlier study, finds heating and cooling, water heating, and other measures to be highly significant. If heating and cooling measures, such as water heaters or furnaces, are installed, the expected rebound effect increases by 53.3 percentage points, all else constant. For water heating measures, the expected rebound effect increases by 41.2 percentage points, all else constant. Other measures include low flow toilets and pool water heaters. For these measures, the expected rebound effect increases by 58.7 percentage points, all else constant. As the rebound effect from low flow toilets in this dataset were low to moderate, ranging from 1-19%, the high increase in expected rebound effect is likely due to the contribution of pool water heaters, which had much higher rebound effects of around 80%. The higher rebound effect from these efficiency measures may be due to a few possible issues. First, there may be unmet need for these services. Households may desire more heating or cooling or hot water than they can afford with inefficient devices. Installing an energy efficient device allows them to better meet their desired use of these services. Second, there may be higher inaccuracy in estimating the actual savings from these measures.

FE (1) finds the comfort factor to be highly significant. Holding all else constant, if a study includes a comfort factor, the expected rebound effect is 36 percentage points lower. The comfort factor is highly significant at the 1% level. This suggests that for this sample of studies, the comfort factor, or amount of the rebound effect attributed to largely consumer behavior change, is about 36 percentage points lower than the overall rebound effect, all else constant. About 36 percentage points of rebound effect estimates might be due to inaccurate engineering estimates of energy savings, implementation issues, performance issues, inadequate program targeting, and other inflating factors. The intercept of the equation is also significant (at the 5% level), suggesting a general rebound effect estimate of 36.9% across studies.

FE (1) suggests that studies focusing on the comfort factor, which largely addresses the behavioral component for energy demand changes after efficiency implementation, find lower rebound effects than others. Comfort factor is caused mainly by behavioral increases in home temperature but part of the temperature rise can be a side benefit from shell improvements, such as insulation and reduced draft. Prediction models may underestimate possible energy savings from temperature improvements after efficiency retrofits. This finding may suggest that current energy savings prediction methods can be further improved to provide more accurate predictions.

A fixed effects model, FE (2) with all twenty studies, was also developed. In FE (2), only heating and cooling efficiency measures, study size, and the constant are significant. Holding all else constant, the presence of heating and cooling efficiency measures increases rebound effect estimates by 33.4 percentage points. By including the outlier study, the coefficient for heating and cooling variable decreases from 0.533 to 0.334 and the comfort factor coefficient is no longer significant. However, sample size is significant at the 10% level. With each increase in study size, the expected rebound effect increases minutely (1.18e-08), all else constant. For the largest sample size of 1.9 million from Davis et al., this translates to an expected rebound effect increase of about 0.02 or 2 percentage points, all else constant. The constant in FE (2) is also significant, suggesting that a general expected rebound effect of 70.8% across studies, all else constant.

FE (2), which includes the outlier study, suggests that energy use changes after heating and cooling efficiency implementation may negate all the expected energy savings from efficiency and may increase the expected energy savings. In cases where heating and cooling measures are installed, the expected rebound effect increases to about 104%. The difference between FE (1) and (2) are substantial and point to the high impact of the outlier study. Larger studies have more influence in a fixed effects models compared to a random effects models (Borenstein, Hedges, Higgins, & Rothstein, 2009). Due to the large study size of over 1.9 million households, the outlier Davis et al. study has a large impact in the fixed effects model.

The F-test in *areg* tests whether all the coefficients except the dummies, in this case individual studies, and the constant are equal to zero (Harbord & Higgins, 2008). We reject this null hypothesis at the 0.05 significance level for both FE models.

The command *areg* also conducts another F-test to test whether all dummy variables are equal to zero in all equations that contain them (StataCorp, n.d.-a, n.d.-b). For the FE (1), which excludes the outlier study, we reject the null hypothesis that all dummy variables are equal to zero at 0.4% significance. Therefore, some individual studies help explain the variation in rebound effect. For FE (2), which includes the outlier study, we fail to reject the null hypothesis that all dummy variables are equal to zero at 97% significance.

2.7.2-2 Impact of Study Size & High Frequency Author

The impact of study size and authorship were also examined. A dummy variable was created to examine the impact authorships. Papers with Hirst, an author on three of the studies, were coded with 1. Two models were created, one using data including the outlier study and one using data excluding the outlier study. See Table 2-4 for these models.

In examining the impact of authorship, I find that the significant variables are not much impacted in comparison to previous models regardless of whether the outlier study is included or not. When the outlier study is included, rebound effect estimates do not significantly differ due to study size. However, when the outlier study is excluded, rebound effect estimates are significantly different between large and small sized studies.

Table 2-4. Fixed Effects Models within Groups by Author

	Variables	(3) No Outlier	(4) Outlier
	Peer Review Publication	-0.22	-0.0657
		(0.325)	(0.571)
	Academic Lead Author	0.107	0.114
		(0.185)	(0.428)
	Academic Study	-0.507	-0.468
		(1.315)	(3.384)
	Study Size	0.000011	1.19e-08*
		(0.000)	(0.000)
	Single Family House	7.55E-02	5.03E-02
		(0.106)	(0.268)
	Control Group	-0.217	-0.475
		(0.265)	(0.475)
	Random Sample	-0.665	-0.792
		(0.445)	(0.906)
	Metered Energy Readings	0.00934	-0.126
		(0.321)	(0.390)
	No Monetary Scheme	-0.185	-0.119
		(0.394)	(0.686)
	Energy Audit	-0.114	-0.0175
		(0.232)	(0.524)
	Preferred RE Estimate	-0.0565	-0.00054
		(0.085)	(0.006)
	Comfort Factor	-0.363***	-0.335
		(0.114)	(0.292)
Efficiency Measures	Heating and Cooling	0.345*	0.334***
		(0.183)	(0.004)
	Water Heating	0.314**	0.254
		(0.153)	(0.326)
	Insulation	-0.109	0.056
		(0.161)	(0.360)
	Weatherization	-0.179	-0.0963
		(0.188)	(0.474)
	Appliances	-0.567	0.0232
		(0.563)	(0.535)
	Windows/Doors	0.103	0.138
		(0.164)	(0.403)
	Programmable Thermostat	-0.0374	-0.0567
		(0.290)	(0.646)
	Lighting	0.0224	0.000636
		(0.291)	(0.720)
	Other Measure	-0.221	0.209
		(0.259)	(0.370)
	Calculation Issues	0.145	0.198
		(0.173)	(0.376)
	Constant	0.676	0.565
		(0.807)	(1.207)
	Observations	139	162
	R-squared	0.457	0.982

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The impact of study size was also considered through different groupings based on study size. Three sets of dummy variables were created. In the first one, the largest studies, Davis et al. (2014) and Henderson et al. (2003), were coded as one. These studies had sample sizes greater than 5000. In the second grouping, studies with sample sizes above one thousand were coded one. In the last dummy variable, studies with sample sizes more than one hundred were coded one. See Table 2-5 for all models pertaining to study size.

Once the outlier study is excluded, different factors are significant when controlling for varied study sizes. Depending on how study sizes are grouped, authorship, study design, calculation issues, and financing are significant in addition to comfort factor and heating and cooling, water heating, and other measures. Results suggests author affiliation may provide bias in rebound effect studies. Author affiliation is significant at the 10% level in model 6.1. Controlling for large or small studies, studies with university affiliated lead authors report higher expected rebound effects, all else constant. This suggests author affiliation may provide bias in rebound effect studies.

Study designs also impact rebound effect estimates. A study with randomly selected participants has lower expected rebound effect estimates, all else constant, after controlling for study size. This is significant at the 1% level in both model 6.1 and 6.2. Issues with calculating potential energy savings during the study also can impact the resulting rebound effect. A study with issues calculating the predicted energy savings from energy efficiency has higher expected rebound effect estimates, all else constant, after controlling for study size (See model 6.2).

Table 2-5. Fixed Effects Models within Groups by Study Size (SS)

		With Outlier		Without Outlier	
		(5) SS >5000	(6.1) SS >5000	(6.2) SS >1000	(6.3) SS >100
Peer Review Publication		-0.0694	-0.547	0.132	-0.051
		(0.557)	(0.372)	(0.403)	(0.340)
Academic Lead Author		0.4	0.596*	0.317	0.0945
		(0.645)	(0.329)	(0.204)	(0.138)
Academic Study		-0.415	-0.235	-0.264	-0.19
		(3.382)	(1.304)	(1.309)	(1.322)
Study Size		1.18e-08*	7.61E-06	8.94E-06	9.31E-06
		-6.58E-09	-1.45E-05	-1.44E-05	-1.44E-05
Single Family House		0.0632	0.13	0.109	0.139
		(0.264)	(0.106)	(0.103)	(0.112)
Control Group		-0.48	-0.257	-0.0752	-0.273
		(0.463)	(0.233)	(0.253)	(0.237)
Random Sample		-0.99	-1.470***	-0.704***	-0.127
		(1.001)	(0.550)	(0.240)	(0.481)
Metered Energy Readings		0.0014	-0.143	0.448	0.305
		(0.388)	(0.249)	(0.390)	(0.326)
No Monetary Scheme		-0.227	-0.912*	-0.213	-0.0754
		(0.694)	(0.513)	(0.252)	(0.265)
Energy Audit		0.055	0.232	0.204	-0.266
		(0.519)	(0.281)	(0.294)	(0.218)
Preferred Estimate		-0.00054	-0.0289	-0.0402	-0.0402
		(0.006)	(0.086)	(0.085)	(0.085)
Comfort Factor		-0.332	-0.342***	-0.388***	-0.369***
		(0.292)	(0.113)	(0.114)	(0.113)
Efficiency Measures	Heating and Cooling	0.334***	0.360**	0.444**	0.336*
		(0.00385)	(0.169)	(0.184)	(0.170)
	Water Heating	0.237	0.318**	0.309**	0.281*
		(0.328)	(0.149)	(0.150)	(0.152)
	Insulation	0.0909	-0.107	-0.151	-0.135
		(0.366)	(0.157)	(0.160)	(0.159)
	Weatherization	-0.088	-0.128	-0.274	-0.201
		(0.446)	(0.173)	(0.184)	(0.172)
	Appliances	-0.342	-0.65	-1.141*	-0.74
		(0.992)	(0.503)	(0.649)	(0.520)
	Windows/Doors	0.152	0.114	0.0482	0.0901
		(0.392)	(0.158)	(0.163)	(0.159)
	Programmable Thermostat	0.0676	0.0427	0.153	-0.0416
		(0.627)	(0.278)	(0.307)	(0.275)
	Lighting	-0.124	-0.138	-0.0754	0.0683
		(0.772)	(0.304)	(0.297)	(0.291)
	Other Measure	0.168	-0.575*	-0.0623	-0.242
		(0.385)	(0.329)	(0.271)	(0.247)
Calculation Issues		0.11	-0.201	0.369*	0.154
		(0.440)	(0.251)	(0.209)	(0.134)
Constant		0.608	1.602*	-0.0794	0.284
		(1.048)	(0.818)	(0.797)	(0.660)
Observations		162	139	139	139
R-squared		0.982	0.469	0.466	0.465

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Lastly, financing for the energy efficiency measures also significantly impacts the rebound effect estimates after controlling for study size greater than 5000. In the studies included in this analysis, the energy efficiency financing schemes focus on free measures, rebates, or zero and low interest loans. Holding all else constant and controlling for study size, studies with no monetary scheme for energy efficiency measures find lower expected rebound effect estimates. This is significant at the 10% level in model 6.1. This finding suggests that having no financing schemes for energy efficiency may realize lower rebound effects in households. Subsidies, though popular, can promote the rebound effect by lowering the effective price of the energy efficient service (Linares & Labandeira, 2010). By lowering equipment cost, energy efficiency subsidies also lower the total cost for each use of the energy service provided by the efficient equipment. Due to the lower cost of the energy services, a rebound effect can occur if the demand for the energy service from the efficient measure increases.

The provision of extrinsic financial incentives may cause unintended consequences. Financial incentives may “crowd out” or undermine intrinsic motivation to engage in conservation efforts (Rode, Gómez-Baggethun, & Krause, 2015). Financial incentives may impair conservation efforts by changing the frame from a social to a monetary one or by decreasing the degree that households view conservation as a pro-social act (Pellerano, Price, Puller, & Sánchez, 2015). Likewise, there may be “moral license” effect, where consumers may believe the implementation of an energy efficient device gives them moral license to increase their electricity consumption in other areas, leading to a rebound effect. Other energy conservation campaigns have found evidence for a moral license effect (McCoy and Lyons, 2016; Tiefenbeck, Staake, Roth, & Sachs, 2013). There is a tension between economic and biospheric appeals when trying to elicit environmental behavior. In tire-check appeals, biospheric and neutral appeals prompted greater compliance than economic appeals. Consumers may "prefer to see themselves as 'green' rather than 'greedy'" (Bolderdijk, Steg, Geller, Lehman, & Postmes, 2013, p. 1). Economic subsidies for energy efficiency may experience a similar tension, with the financial incentives reducing the "warm glow" from efficiency implementation and impacting further pro-environmental behavior. Certain subsidy designs may help ameliorate the impact of a moral license effect. In their evaluation of four California utility energy efficiency programs, Brown and Mihlmester found a median realization rate of 1.06 for residential shared-savings incentive programs (1995). Since actual program savings were similar to predicted savings, shared savings incentive programs may be effective in counteracting rebound effects and moral license. More studies on how subsidies impact the rebound effect and consumer energy behavior are needed and may lead to improvements in energy savings as we better understand consumer responses.

The findings in this chapter suggest that the way many utility programs are conducted, with targeted populations and rebates or other financial incentives, likely realize higher rebound effects and lower average energy savings per household than if participants are randomly selected and no financial incentives are provided when efficiency measures are installed. Improved program targeting may improve energy savings from utility programs. This study finds evidence that programs with random selection of participants have lower expected rebound effects. This suggests that current targeted participation selection for energy efficiency programs may impact realized rebound effects. Allcott, Knittel, and Taubinsky find utility subsidies are adopted by "wealthy environmentalist homeowners." Some utilities target previous program participants and environmentalist households due to a higher likelihood of efficiency implementation. Such efforts may not be economically efficient with greater welfare gains possible with improved targeting (Allcott, Knittel, & Taubinsky, 2015).

Currently, most studies appear to examine the impact of energy and renewable energy subsidies. Studies examining energy efficiency subsidies generally focus on either the uptake of the subsidized energy efficiency technologies, projected energy impacts of subsidies, or their impact on lower quality goods (Ameer & Krarti, 2016; Nauleau, Giraudet, & Quirion, 2015; Yang & Zhao, 2015). Few studies examine the subsequent energy demand impacts of energy efficiency subsidies after efficiency implementation within actual households. Also, due to the lack of consistent verification that energy efficiency investments have paid off as expected (Palmer, Walls, Gordon, & Gerarden, 2013), future energy efficiency studies may desire to examine energy efficiency investments and their impact on rebound effects. Further research on the impact of energy efficiency subsidies on post implementation behavior is warranted.

Due to the limited study size of this meta-analysis, further studies are needed to explore and confirm how energy efficiency financing for energy efficiency and study designs impacts household energy behavior after efficiency installation. However, if this effect is confirmed, the impact of financing options and study designs on post implementation energy consumption should be considered in future analyses of energy policies and energy efficiency programs. It may have significant impacts on the realized energy savings from energy efficiency implementation.

Though there have been decades of energy efficiency literature, this meta-analysis finds only a handful of quasi-experimental residential studies that provide enough information to be included. There are many energy efficiency studies that fail to predict the expected energy savings from efficiency measures and measure only pre and post energy use. Whereas past studies criticized the quasi-experimental literature for its methodological weaknesses, this study sheds light on specific areas of the quasi-experimental studies that may especially impact rebound effect. Further studies are needed to explore and confirm how energy efficiency financing for energy efficiency impacts household energy behavior after efficiency installation.

2.8 Policy Implications

There is a need for more empirical research about energy efficiency and the rebound effect, especially multi-disciplinary efforts between engineers and social scientists. With advancements in smart homes and devices, engineers should be able to gather tailored data more easily for more accurate calculations of potential energy savings. Engineering efforts must be combined with social science knowledge and consumer behavior research to further residential energy research. Policies can support such interdisciplinary research efforts.

Government funded energy efficiency studies should require a consistent reporting convention that allows easy estimation of rebound effect and pertinent statistical information. The followings should be documented:

- participant recruitment methods and total sample size,
- applied energy efficiency measures,
- efficiency levels pre and post energy efficiency upgrades,
- measured energy consumption before and after retrofits for each household,
- measurement methods and associated errors,
- standard deviations for sample measurements, and
- predicted savings calculation method and assumptions.

All energy efficiency studies should be encouraged to adhere to this convention, but government funded studies can be mandated to provide it. By reporting the same information across studies, researchers enable their research findings to be included in future meta-analyses.

If efforts are coordinated globally, a consistent protocol and large database of energy research may more quickly enable data improvements and understanding of consumer energy behavior. Past researchers have also recommended developing a protocol for energy efficiency studies and a large database (Sanders & Phillipson, 2006), but these efforts, if any, are not well publicized. Coordinating research efforts will improve the accessibility and usability of research findings to inform policymakers and future researchers. Future meta-analyses would be easier to conduct and any discord regarding energy efficiency and rebound effects can be better alleviated.

Social science contributions to quasi-experimental research may be especially important in understanding the policy implications from different program and subsidy designs. Current quasi-experimental research focus on examining the impact of energy efficiency on household energy demand. Many studies fail to predict the expected savings beforehand, focusing instead on the energy saved compared to pre-implementation levels. However, if research designs and subsidies impact the magnitude of the rebound effect, then these issues can significantly impact the realized energy savings and have implications for how energy efficiency policies and programs are designed and implemented. By also examining the impact of program and subsidy design within quasi-experimental research, we will garner more information on how consumer energy demand reacts towards such levers. Though the findings in this study is based on a small sample, its findings, especially if confirmed in future quasi-experimental research, may have significant impact on future energy efficiency program and policy designs. It warrants further exploration and research.

Likewise, further examination on the impact of subsidies for energy efficiency is warranted. This meta-analysis finds evidence that suggests subsidies may increase rebound effects in current energy efficiency studies. However, much current literature on energy efficiency subsidies focus on the impact of subsidies on uptake of energy efficiency technologies or free ridership. Few studies examine the impact of subsidies on within household energy use before and after implementation (Alberini & Bigano, 2015). This may be because current concepts of success for subsidy programs focus on the uptake of energy technologies and the cost of implementation. Little notice is given to the impact of subsidies on post implementation energy use. Further examination of the impact of various energy efficiency subsidies on residential energy behavior and the subsequent rebound effect is warranted. Research results will have significant policy implications and may suggest which subsidies are better suited to energy demand goals.

By combining engineering and social science insights, a holistic understanding of energy efficient technology and consumer behavior can be developed, one that may foster new technologies focused on providing convenience, comfort and energy savings to residential consumers. Policymakers can leverage improved understandings of the rebound effect to support new smart residential technologies. Policies can encourage the development of energy efficient technologies that better meet the demands of more air-tight and efficient homes (Bell & Lowe, 2000). Technology design matters in how much energy use is automatic or user controlled (Bladh, 2011). Policies can support the development of technologies with more automated features. Not only will consumers have greater convenience, but utilities will also have more predictable energy demand as fluctuations in energy use are reduced.

2.9 Conclusions

Time has not decreased the vitriolic arguments over the rebound effect and whether energy efficiency saves energy. This study aims to contribute to the discussion through a meta-analysis of quasi-experimental household studies. In total, twenty studies in eight countries provided 162 estimates of rebound effect. One study was an outlier in its large study size. Once this study is excluded, the remaining 19 studies provided 142 estimates of rebound effect. Though the majority of the rebound effect estimates were below 100%, there was variation in estimates within and between studies.

In conducting this meta-analysis, the dearth of quasi-experimental literature allowing rebound effect estimates was clearly evident. Only twenty studies were located. Though many energy efficiency studies are available, not all studies predict savings beforehand and report information to allow the rebound effect to be estimated. Many estimates of rebound effect also lack statistical information. Due to the missing information regarding standard deviations and standard errors, the presented analyses were weighted by study size, allowing larger studies to have more weight.

A random effects model of study level estimates of rebound effect finds an average rebound effect estimate of 42%, with high heterogeneity between studies. This average value for rebound effect is moderately high, but still less than 100%. Therefore, the study level random effects model does not find evidence of average rebound effects with backfire. Energy efficiency, on average, saves energy after implementation even after accounting for the rebound effect. Random effects meta-regression models did not find significant factors, likely due to the small number of studies in this analysis. Therefore, study factors impacting rebound effect estimates could not be examined in a random effects model.

Instead, fixed effects models were created to examined the impacts of various factors. Since the fixed effects models cannot account for the variation in study designs, which was large in this sample, these results should be considered cautiously. Future researchers should revisit this with larger studies providing more statistical information or explore these issues in quasi-experimental studies. Several fixed effects models were created that examine different groups: individual studies, large and small sized studies, and high frequency author studies and other studies.

Rebound effect estimates vary based on the efficiency measures that are implemented. Heating and cooling measures and water heating measures are significant factors in all three fixed effects models excluding the outlier study. The presence of heating and cooling efficiency measures increases expected rebound effect from 35-53 percentage points higher, all else equal. The presence of water heating measures increases expected rebound effect from 31-41 percentage points higher, all else equal. The increase in rebound effect for these two end uses suggests that there might be unmet demand for heating, cooling, and water heating services.

This study also finds a difference between studies focused on examining comfort factor, which focuses mainly the behavioral change after efficiency, and general rebound effect estimates in models excluding the outlier study. Studies that examine comfort factor find rebound effect estimates that are 34-36 percentage points lower than general studies of rebound effect, all else constant. Since comfort factor focuses largely on energy increases from consumer behavior, the 34-36 percentage point difference may be due to inflating factors like issues with predicting savings, implementation, and performance. This suggests calculation methods for predicted savings may need improvement.

After controlling for study size (large or small), this study also finds author affiliation, study design, and financing options measures significant in rebound effect estimates. After controlling for study size, studies with university affiliated lead authors have higher expected rebound effects, all else constant. Studies with randomly selected participants have lower expected rebound effect estimates when study size is controlled, all else constant. These suggest that author affiliation and method of selecting participants may bias rebound effect estimates. Studies that did not offer financing options have lower expected rebound effects after controlling for study size, all else constant. This suggests that special financing measures for energy efficiency, such as low or no interest loans, rebates, and free measures, may impact consumer energy behavior after implementation. Further research on how study designs and financing options for energy efficiency measures impact consumer energy behavior after implementation is needed. If this impact is confirmed, then these impacts should be considered when designing energy policies and programs for they have significant implications for energy efficiency programs and policies.

There is a need for more empirical research about energy efficiency, the rebound effect, and household energy behavior. Likewise, and perhaps even more importantly, a consistent reporting convention should be created to include data and statistical information applicable to multiple energy researchers so findings can be used by a range of energy scholars. For instance, participant recruitment methods, measured energy consumption before and after retrofits, predicted savings, and measurement methods are just a few of the items that should be included in such a protocol. By reporting the same information across studies, researchers enable their research findings to be included in future meta-analyses and can contribute to other ongoing energy discussions. Gathering all such energy research into a large database would only further the ease of access, contributions to other energy research, and dissemination of results. Past researchers have also recommended developing a protocol for energy efficiency studies and a large database (Sanders & Phillipson, 2006), but these efforts, if any, are not well publicized. Coordinating research efforts will improve the accessibility and usability of research findings to inform policymakers and future researchers. Future meta-analyses would be easier to conduct and have larger sample sizes. Such efforts would help alleviate discord regarding energy efficiency and rebound effects.

Lastly, engineers should combine efforts with social scientists to design energy efficiency studies. How technologies improve energy efficiency is entirely technical, but how consumers use them at home is not. A multi-disciplinary team will be better able to study all aspects of how consumers interact with energy efficient technologies and the policy impacts and implications. Engaging households to allow access to their homes and energy information is challenging and it may be difficult for energy research within actual households to go beyond quasi-experimental designs. However, it is essential that we understand consumer energy behavior. Limiting ourselves to large economic studies based on historical energy data will never allow us to understand the intricacies of household energy decisions and behavior. We cannot ignore the contributions of the quasi-experimental literature. Apprehensions regarding its methodological weaknesses should instead motivate better and improved research. A holistic multi-disciplinary understanding of how consumers, technology, and energy interact will not only inform energy policies, but also help create improved energy efficient designs.

The rebound effect is an uncomfortable topic, one that has been overlooked in the past (Sorrell, 2009). Faced with evermore dire climate change predictions, we must understand how people respond to energy efficient technologies to create effective environmental policies. The topic, regardless of how uncomfortable, needs to be met head on with better and more research. The heated debates about rebound effect and energy efficiency can only be cooled by real-world evidence. The implications for our environment and world are too significant for us to muddle forward without fully understanding consumer energy behavior. Understanding our daily energy decisions should be a building block in addressing the climate challenges we face. Our energy decisions at home matter and in a big way.

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CHAPTER 3. THE IMPACT OF SMART GRID PROJECTS AND OTHER FACTORS ON RESIDENTIAL ENERGY DEMAND

3.1 Introduction

Innovation in electricity generation and transmission in the U.S. have long stagnated. Electrical generation efficiency did not increase for more than half a century and transmission cables are still largely 1950s technology facing significant electrical transmission losses (M.A. Brown, 2007). Recent energy policy has focused on upgrading current electrical grids. The American Recovery and Reinvestment Act (ARRA) of 2009 provided \$4.5 billion in grid modernization support. With a match of over \$5.5 billion in private sector funds, grid modernization funds totaled over \$10 billion. In June 2011, smart-grid development in rural U.S. received an additional \$250 million in loans (U. S. Department of Energy, 2011). As more information technology capabilities are incorporated, electrical grids become "smarter" and are commonly referred to as "smart-grids."

Of the two types of information technology currently incorporated into the electrical grid, automated meter reading (AMR) and advanced metering infrastructure (AMI), only AMI is essential to smart grid development. AMR uses one-way communication to collect and transmit usage information from customer to the utility for billing purposes (U.S. Energy Information Agency, n.d.). AMI uses two-way communication to not only measure and record usage from customers, but to also deliver this information to customers more frequently than the monthly electric bill (U.S. Department of Energy, n.d.; U.S. Energy Information Agency, n.d.). Utilities are moving away from AMR technologies, which cannot support demand-side management due to one-way communication, to focus on AMI technologies, which enable the transition to smart grid (Farhangi, 2010). By the end of 2014, 51.7 million residential customers had AMI and 41.8

million residential customers had AMR. In total, these technologies serviced 41% and 33% of all residential electrical meters, respectively (U.S. Energy Information Administration, 2015). By the end of 2015, an estimated 65 million smart meters, an integral part of AMI, servicing over a third of electricity customers, were to be installed (U. S. Department of Energy, 2014).

The large financial investments in smart grids were made based on claims that they would improve utility operations, improve customer information and subsequent energy use, and enable a clean energy economy. At the time of the ARRA, "there was very little data from actual smart grid deployments to back up [these] claims" (U.S. Department of Energy, 2011), despite over thirty years of household energy consumption research (Dubin, Miedema, & Chandran, 1986; Hayes & Cone, 1977; Quigley, 1984; Seligman & Darley, 1977; Shin, 1985; Stern, Dietz, Gardner, Gilligan, & Vandenbergh, 2010).

Previous research focused largely on pilot studies and a sample of usually one utility's customers. No studies, to the author's knowledge, focuses on examining actual deployments of smart grid across utilities. Of the utilities with AMI programs, how has residential electricity consumption been impacted? How do other utility specific factors, such as customer demographics, geographic variables, and local cultural characteristics, impact utility residential electricity demand?

This work estimates a model of average consumer electricity demand at the utility level to better understand how AMI and other factors impact residential electricity demand. It adopts the simplified model of the "reduced form model of behavioral public finance" from Allcott and Sunstein (2015) and Mullainathan, Schwartzstein, and Congdon (2012) to examine how information biases impact residential electricity use. This work seeks to inform a better understanding of AMI impacts and socio-physical variables effecting utility level electricity use.

First, literature about consumer behavior are discussed. Next, the data and methodology are described, followed by results, discussion, and conclusions.

3.2 Literature Review

As the understanding of human behavior improves, it has been incorporated into consumer models that blend social, psychological, and economic approaches to be more comprehensive (Czap & Czap, 2010; Hargreaves, Nye, & Burgess, 2013; Hori, Kondo, Nogata, & Ben, 2013; Sahakian & Steinberger, 2011; Sardianou, 2007; Thogersen & Gronhoj, 2010; Urban & Scasny, 2012). By examining sociological and psychological factors in economic frameworks, these studies further knowledge of human behavior and behavioral economics. This work continues these efforts by studying consumer electricity use and the impact of information.

3.2.1 Consumer Bias and Additional Information

Behavioral economics includes insights from other social sciences, especially psychology, to examine markets with consumers that have human limitations (Diamond & Vartiainen, 2012; Mullainathan & Thaler, 2000; Sent, 2005). Humans deviate from the standard economic model due to bounded rationality, bounded will power, and bounded self-interest. Not only is human problem solving constrained by limited cognitive abilities (bounded rationality), it is also impacted by the propensity to make choices that are not in one's long term interest (bounded will power) and a willingness to sacrifice self-interest to assist others (bounded self-interest) (Mullainathan & Thaler, 2000). Though there have been radical technological innovations in information, data storage, and communication, frameworks for attention and decision making have remained much the same (van Knippenberg, Dahlander, Haas, & George, 2015). Theories of bounded rationality describe constraints on consumer information processing abilities (Simon, 1972). Two theories of bounded rationality in particular pertain to this work.

First, rationality may be bounded by incomplete information regarding alternatives or consequences. The information available to the consumer is determined by the amount of resources dedicated towards searching for alternatives or consequences (Simon, 1972). Second, rationality may be bounded by complexity, where environmental factors limit the consumer's ability to select the best choice (Simon, 1972), such as institutional, social, and psychological factors that can substantially impact human decision making and cognition (Bertrand, Mullainathan, & Shafir, 2006).

Residential decision-making is limited by lack of information (Carrico et al., 2010; Gardner & Stern, 2008). The invisible nature of electricity use also complicates the issue. Consumers are interested in energy services, which electricity supports. It may be difficult for consumers to link the activities involved in electricity use, as varied as selecting appliances, listening to music, and calling a friend, with a coherent and comprehensible cognitive frame (Fischer, 2008). When provided feedback on their consumption, residential consumers decreased energy use (Matsukawa, 2004). Empirical studies on consumption feedback to residential households finds it decreases subsequent use by as much as 5-10% (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Matsukawa, 2004; Seligman & Darley, 1977).

Consumers are also influenced by the decisions of others (Kasanen & Lakshmanan, 1989). However, the impact of information with social norms, group feedback (e.g. like for all households in a city), or comparison with other households can be mixed. In their meta-analysis of social influence approaches, Abrahamse and Steg find smaller impacts from these types of information than face to face interactions in impacting resource conservation. This may be due to the differing impact of such information, depending on the subgroups. If participants already conform to the desired action, there may be a boomerang effect, where low resource users increase their use with the additional information, while high resource users decrease their use with the additional information (Abrahamse and Steg, 2013). In studies of OPower home energy reports with peer comparison, electricity decreased by 1.2-2.1% and was sustained or increased as time went on (Allcott, 2011b; Ayres, Raseman, & Shih, 2013). After two years of home energy reports, the reports still impacted household energy behavior. The effects from receiving such additional home energy information showed persistence, with decay of 10-20% after cessation after two years of treatment (Allcott & Rogers, 2014). Electricity use declined nearly 1% with information comparing household electricity use with a benchmark neighbor. When information on financial incentives were included with the information, the impact of social comparison was negated, suggesting there may be a conflict between monetary and non-monetary information measures in reducing consumer energy use (Pellerano, Price, Puller, & Sánchez, 2015). There is evidence that financial incentives may "crowd out" or undermine intrinsic motivation to engage in conservation efforts (Rode, Gómez-Baggethun, & Krause, 2015).

Residential consumers may not be fully informed on electricity prices. Shin finds residential consumers responded to the perceived average electricity price from their bills. When an incorrect perceived average price is corrected with information, substantial changes in demand may occur (Shin, 1985). After examining water bills from 383 utilities for 1995 in an aggregate water demand model, Gaudin found a 30% or more increase in price elasticity when additional price information was added to bills. The impact of additional price and quantity information on water bills are examined through dichotomous variables interacting with the price variable (2006). Jessoe and Rapson also found increased price elasticity of demand in consumers exposed to more frequent electricity usage information (Jessoe & Rapson, 2014). As price elasticity becomes more negative, demand decreases more as prices increase. At the same time, demand increases more as prices decrease.

Not all additional information decreases energy use. In an experiment when normative messages were provided to residential consumers comparing their energy use with the average use of the neighborhood, Schultz et al. find a boomerang effect on electricity use. Households using more than the average reduced their electricity use while households using less than the average increased their electricity use. Once an injunctive message of a smiling or sad face was added, the boomerang effect was eliminated. In these cases, households consuming less than the average did not change their electricity use (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). This suggests that how information is designed and relayed can significantly impact residential electricity use.

Mullainathan et al. put forth a reduced form approach to behavioral modeling that addresses the fragmented and diverse findings from behavioral economics in a parsimonious framework (2012). Allcott and Sunstein further simplify this approach to describe the impact of consumer bias on demand (2015). In their framework, individuals decide whether to take action with an equilibrium price p and a perfectly competitive supply curve $S(p)$. A bias parameter, b, is introduced to represent a number of the biases from behavioral economics. Normally, consumers act when their utility, v, is greater than the price, p. The market demand in this case is represented by $D_M(p)$.

In the behavioral model, consumers act when their decision utility ($v - b$) is greater than p, where b can be negative, zero, or positive. In a case where $b > 0$, the unbiased market demand is represented by $D_U(p)$. The vertical distance between $D_M(p)$ and $D_U(p)$ is bias b, quantified in dollars (Allcott & Sunstein, 2015). See Figure 3-1 for a graphical depiction of this simplified reduced form approach of behavioral modeling.

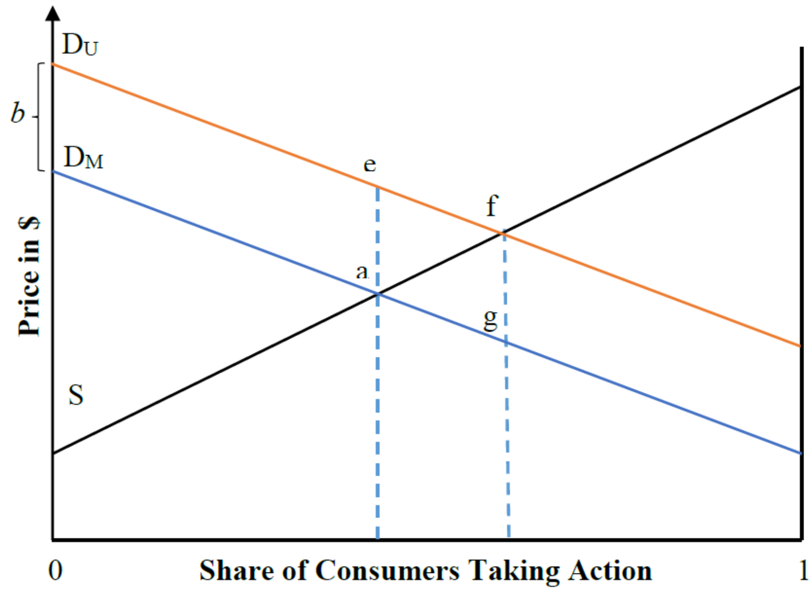

Figure 3-1. Reduced Form Approach to Behavioral Modeling
(Adapted from Allcott & Sunstein, 2015)

As seen in Figure 3-1, the bias from consumer imperfections, such as the lack of full information, leads to a reduced share of consumers taking that action in the market. When the bias is corrected, the share of consumers taking the action increases. Previous studies have tried to measure the bias from imperfect information empirically by providing information to treatment groups (Allcott & Sunstein, 2015). Similarly, information feedback programs provided by AMI reduces bias by providing additional and readily accessible information. Therefore, these programs likely increase demand for energy efficiency or conservation and decreases electricity use according to the reduced form approach to behavioral modeling. The following hypotheses are formed based on these insights and previous research findings.

Hypothesis 1 (H1): More AMI installations, which enable the provision of detailed energy information, decreases average household electricity use, controlling for weather, socio-demographic factors, suburbia, and year time trends.

Hypothesis 2 (H2): More frequent energy pricing information from time response programs decreases average household electricity use, controlling for weather, socio-demographic factors, suburbia, and year time trends.

3.2.2 Price Elasticity Impacts

Price elasticity of demand ($\boldsymbol{\varepsilon}$) describes the relationship between price and quantity demanded. It is the percentage change in quantity, $\boldsymbol{q}$, over the percentage change in price, $\boldsymbol{p}$**.**

$$\boldsymbol{\varepsilon} = \frac{\Delta \boldsymbol{q}/\boldsymbol{q}}{\Delta \boldsymbol{p}/\boldsymbol{p}}$$

An accurate estimate of price elasticity allows estimation of how long policy goals take to be realized (Baek, 2011). The information smart grid provides to consumers are expected to inform changes in their consumption of energy. Short run price elasticity focuses on consumption changes, while long run price elasticity also includes equipment stock changes (Gillingham, Newell, & Palmer, 2009). In the case of smart grid, short-run price elasticity is of main interest.

Price elasticity shifts with evolving consumer behavior and structural changes, such as changing land-use patterns, social characteristics, and vehicle trends (Hughes, Knittel, & Sperling, 2006). In the case of gasoline demand, U.S. consumer price elasticity differs considerably due to these issues. Short-run price elasticity values range from -0.21 to -0.34 during 1975-1980. During 2001-2006, these values decreased, ranging from -0.034 to -0.077 (Hughes et al., 2006). Consumers became less responsive to price increases in 2001-2006 compared to 1975-1980. Smart grid technologies provide a structural change, one that can increase consumer price elasticity of electricity demand (Allcott, 2011).

3.2.3 Community Factors

Increased complexity within households, such as reduced time to research and consider alternatives, from environmental factors can limit the capacity to find optimal solutions. Past research suggests that individuals with less time may increase energy use due to limited time resources dedicated to making optimal energy decisions and by relying on emotions instead (Finucane, Alhakami, Slovic, & Johnson, 2000). This is an aspect of bounded rationality (Simon, 1972). It is expected that communities with more time constraints, such as those with higher average commutes to work, will consume more electricity due to less time resources committed to more optimal energy choices.

Consumer environments, from country of residence to household characteristics, can affect behavior (Bowles, 1998). Isenhour finds evidence of more economic, market, social, and political barriers to environmental actions than lifestyle and informational barriers (2010). Thogersen and Gronhoj suggest socio-structural changes can support reductions of household electricity use (2010). Individuals in countries with higher energy intensity have higher willingness to pay for environmental quality (Owen & Videras, 2006). Residents of green communities use more sustainable travel compared to other communities, controlling for demographics and the built environment (Kahn & Morris, 2009). Residents drive less and walk or bike more in areas with high residential density, land use mix, connectivity, and transit access (Frank, Greenwald, Winkelman, Chapman, & Kavage, 2010; Saelens, Sallis, & Frank, 2003). Metro areas with higher density, development concentration, and rail transit have, unsurprisingly, lower per capita carbon emissions (Brown, Southworth, & Sarzynski, 2009). Many of the pro-environmental behaviors appear to be supported by dense urban developments with access to public transportation. It is possible that residents of green communities elect to make more sustainable choices due to the availability of environmental information in these communities.

Hypothesis 3 (H3): Utilities in communities with more readily available environmental information have lower average household electricity use than those in other communities, controlling for weather, socio-demographic factors, suburbia, and year time trends.

Hypothesis 4 (H4): Utilities in communities with higher commute times will have increased average household electricity use, controlling for weather, socio-demographic factors, suburbia, and year time trends.

3.2.4 Impact of Socio-Demographic Factors on Energy Demand

Sociodemographic variables impact consumer energy and environmental decisions. Yue, Long, and Chen find sociodemographic characteristics (age, gender, income, household structure, and education) are important factors impacting energy saving behavior (2013).

The effect of income on energy and environmental decisions is mixed. Low income families focus on income limitations when making energy decisions (Sahakian & Steinberger, 2011). Since energy services represent a larger portion of their budget, these families are constrained in daily energy use and equipment purchases (Cayla, Maizi, & Marchand, 2011). Low income households are more likely to prioritize economic growth over energy conservation and environmental protection (Owen & Videras, 2006). In general, low income families focus more on energy reduction while high income families focus more on energy efficiency. High income families are also more likely to have the means to purchase and implement efficiency measures (Nair, Gustavsson, & Mahapatra, 2010; Yue et al., 2013).

With higher household income, considerations beyond economics enter into energy decisions. Social and cultural factors, such as comfort and fashion trends, impacted air conditioning use in Manila at higher income levels (Sahakian & Steinberger, 2011). Black, Stern, and Elworth find an indirect impact of income, largely through home ownership, on increasing efficiency investments (Black, Stern, & Elworth, 1985). As income increases, electricity use and carbon dioxide emissions also increase (Baiocchi, Minx, & Hubacek, 2010; Wilson, Tyedmers, & Spinney, 2013; Yohanis, Mondol, Wright, & Norton, 2008).

The impact of age varies. In China, age increased the adoption of energy conservation methods and decreased the likelihood of adopting energy efficiency options (Yue et al., 2013). In Greece, age is negatively associated with willingness to adopt energy conservation strategies (Sardianou, 2007). Gronhoj and Thogersen find households with young children have the highest per household electricity use, followed by households with teenagers and households with older couples. At the same time, households with children have the lowest per person usage, those with older couples used slightly more, and households with teenagers have the highest electricity use per person (Gronhoj & Thogersen, 2011).

3.3 Electricity Demand Model and Data

In this paper, an aggregate electricity demand model is estimated, based on the conventional demand function from classical consumer theory where demand is a function of price and income is the base (Reiss & White, 2005). The functional form and variables included are informed by previous studies, data limitations, and areas of interest for this study.

Several variables that may impact the information bias are included. The main variable of interest is AMI penetration in the residential sector. More Leadership in Energy and Environmental Design (LEED) certified buildings are included as a factor possibly increasing available energy information. Commute time is also included to estimate how limited time impacts consumer energy decisions. As commute time decreases, consumers have less available time for energy information and decisions.

Variables controlling for the suburban nature of a utility's service area are included, such as public transportation use, age of the housing stock, percentage of detached houses, and owner occupancy. Socio-economic variables, like average household income, percentage of the population below 18, the percentage of the population 65 and above, and average residential electricity price for the utility are included as control variables. Lastly, weather and year effects are included as control variables. The following modified demand model is estimated:

$$\ln(Q) = \alpha_1 AMI + \alpha_2 AMI + \alpha_3 \ln(LEED) + \alpha_4 T + \alpha_5 PT + \alpha_6 OC + \alpha_7 DH + \alpha_8 MY + \alpha_9 AGE_{18} + \alpha_{10} AGE_{65} + \alpha_{11} \ln(P) + \alpha_{12} I + \alpha_{13} CDD + \alpha_{14} HDD + \beta_i Y_i + \varepsilon$$

where *AMI* is the percentage of residential customers with AMI, *LEED* is the number of LEED certified buildings in a state per capita, *T* is the mean travel time to work, *PT* is the percentage of workers taking public transportation, *OC* is the percentage of owner occupants, DH is the percentage of detached homes, *MY* is the median year built for housing, AGE_{18} is the percentage of population under 18, AGE_{65} is the percentage of population 65 and over, *P* is the average annual residential electricity price, *I* is the average household income, *CDD* is the annual cooling degree days, and *HDD* is the annual heating degree days, Y_i is the vector of dummy coefficients for year effects, and ε is the unobservable characteristics.

3.3.1 Data Sources and Description

This study examines utilities with advanced metering projects from 2009-2013 in the 48 contiguous states. It is an unbalanced panel dataset with 3,004 unique utilities from 2009-2013. Not all utilities have information available for all years.

Data for the smart grid analysis were collected from online data sources. Utility and pricing data were from the Energy Information Administration (EIA) Form 861. The ARRA of 2009 funded many projects through Smart Grid Investment Grant Projects (SGIG) and Smart Grid Demonstration Projects. There are 70 utilities with a total of 87 SGIG projects covering 42 states affecting the residential sector. There are also an additional nine Smart Grid Demonstration Projects with a residential aspect ("Recovery Act Project Information," n.d.). Due to the limited number of ARRA funded projects, this study examines all residential smart grid projects implemented in the U.S. with available EIA data from 2009-2013 without restriction to only ARRA funded projects.

Census data were used to obtain a representative consumer for each utility. Demographic data are from the American Community Survey (ACS) 5-Year Estimates. The 5-year estimates were selected due to the greater data availability for smaller populations, even though it is not the most current data (U.S. Census Bureau, 2015). Several data tables were used from the ACS.[1] The study is limited to 2009-2013 due to the availability of the ACS 5-year estimates.

Counties within each utility's service area were obtained from EIA Form-861 (Service Territory). Census data for each of these counties were located from the ACS 5-year estimates. Data for service area counties were then averaged to obtain representative utility values. In some

[1] ACS data tables that were used are: DP04 Selected Housing Characteristics, DP05 ACS Demographic and Housing Estimates, B25035 Median Year Structure Built, B25010 Average Household Size of Occupied Housing Units by Tenure, S1902 Mean Income in the Past 12 Months, S0802 Means of Transportation to Work by Selected Characteristics.

cases, no census data were available for certain counties. These counties were then excluded and only the counties with available data were used to generate the utility level demographic data.

Heating and cooling degree days for each state are from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (National Climatic Data Center, 2015). Weather information for Washington D.C. is obtained from Weather Underground ("Weather History from KDCA.," 2015). Cooling and heating degree days are calculated by summing the difference between the daily mean temperature and a base temperature of 65°F over any period of interest. Heating degree days arise when mean daily temperature is below 65°F. Cooling degree days arise when mean daily temperature is above 65°F (NOAA, 2005).

The LEED certified buildings per capita in the state of operation is also included as another measure of available information on building energy use. LEED certification is a voluntary process, where new and retrofit buildings meeting certain prerequisites earn points to reach different certification levels (certified, silver, gold, and platinum). Buildings with LEED certification distinguish themselves and their use of environmental building strategies and practices ("LEED," 2015).

3.3.2 Data Caveats

Examining average household electricity usage at the utility level presents several challenges. The first challenge is from examining a utility's electricity demand as the aggregation of individual household energy demand, a constraint presented by the available data. It is possible that impacts of household specific socioeconomic factors, such as income and composition, on residential electricity use are weakened when aggregated at the utility level. By studying average residential electricity use in a utility, this study is limited to examining the impact of average electricity price in the utility. Even though studies show consumers respond to average price for electricity demand (Shin, 1985; van Helden, Leeflang, & Sterken, 1987), families may not necessarily experience the be that the average electricity price in a utility, especially with the recently proliferation of different pricing options (such as conventional, green electricity, and time response). Second, the impacts of specific utility programs, especially relatively new programs like AMI with low penetration rates, may be diluted or lost when averaged across the utility.

Lastly, there are limits to the level of detail in the data when aggregated at the utility level. For instance, in the case of the time response variable, the number reflects the percentage of residential customers that participate in time response programs. However, these types of programs include: time of use pricing, real time pricing, variable peak pricing, critical peak pricing, and critical peak rebate (U.S. EIA, 2015a).

3.4 Methodology

Three different methods were compared in developing the model: ordinary least squares (OLS), fixed effects (FE), and random effects (RE) models clustered by utility operation. OLS and FE were compared using the F-test. FE and RE models were compared using the Hausmann test, as is commonly used (Baltagi, 2013). Based on these tests, the FE model was selected.

3.4.1 Variables Considered

Table 3-1 presents the examined variables, their abbreviations, and descriptions.

Table 3-1. List and Description of Variables

Abbreviation	Description
ln(KWH)	Natural log of average household electricity use (kWh/yr).
AMI	Percentage of residential customers with AMI (decimal), lagged by one year.
Time Response	Percentage of residential customers with time response programs (decimal), lagged by one year.
ln(LEED Buildings)	Natural log of LEED buildings in a state per capita.
Commute Time	Mean travel time to work (hours).
Public Transportation	Percentage of workers taking public transportation (decimal).
Owner Occupants	Percentage of all households that are owner occupants (decimal).
Detached Houses	Percentage of detached houses (decimal).
Median Year Built	Median year built for housing stock.
Population under 18	Percentage of population under 18 years of age (decimal).
Population 65 and over	Percentage population 65 years old and older (decimal).
ln(Electricity Price)	Natural log of the mean electricity price per utility.
ln(Average Income)	Natural log of mean household income.
CDD	Cooling degree days by state (in thousands of degree days).
HDD	Heating degree days by state (in thousands of degree days).
2010	Dummy variable for 2010.
2011	Dummy variable for 2011.
2012	Dummy variable for 2012.
2013	Dummy variable for 2013.

3.5 Results & Discussion

This works examines the impact of smart grid programs and socio-physical factors on utility residential electricity use. Table 3-2 reports the average residential electricity demand models for OLS, FE, and RE models. There are 7,459 observations with 2,730 utility operations studied by all models. All three models are substantially different. The FE model is compared with the RE model using the Hausman test (test statistic = 913.21, Prob>$\chi^2 = 0.000$). We reject the null hypothesis that the RE adequately models the utility-level effects. The current specification of the RE model is biased and we select the FE model.

Table 3-2. Estimation Results of Average Utility Residential Electricity Demand, 2009-2013

VARIABLES	(1) OLS	(2) FE
AMI	0.160***	-0.00905**
	(0.0100)	(0.00376)
Time Response	0.253***	0.0189
	(0.0457)	(0.0169)
ln (LEED Buildings per Capita)	-0.0916***	-0.00564
	(0.00642)	(0.00383)
Commute Time	0.304***	-0.0298
	(0.0562)	(0.0353)
Public Transportation	-0.580***	0.802**
	(0.1980)	(0.3310)
Owner Occupants	-0.253***	-0.486***
	(0.0805)	(0.0911)
Detached Houses	-0.0566	-0.0142
	(0.0577)	(0.101)
Median Year Built	0.00318***	-0.00421***
	(0.000398)	(0.000920)
Population < 18	0.459***	0.821***
	(0.147)	(0.259)
Population $\geq$ 65	0.966***	-0.201
	(0.153)	(0.273)
ln Electricity Price	-0.549***	-0.176***
	(0.0125)	(0.0135)
ln Average Income	-0.0903***	0.277***
	(0.0203)	(0.0334)
CDD	0.0749***	0.0984***
	(0.00817)	(0.00422)
HDD	0.00435	0.0485***
	(0.00356)	(0.00203)
2010		0.00701
		(0.00565)
2011	0.0601***	0.00841**
	(0.00771)	(0.00377)
2012	0.0766***	-0.00679**
	(0.00962)	(0.00289)
2013	0.138***	
	(0.01050)	
Constant	4.116***	14.81***
	(0.837)	(1.826)
R-squared	0.339	0.395

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

3.5.1 Utility Programs

3.5.1-1 Advanced Metering Infrastructure

The coefficient for AMI varies in sign when moving from the OLS to FE model. In the OLS model, the coefficient is positive, suggesting that AMI increases average residential electricity use in a utility. Once within utility time-invariant effects are controlled by the FE model, the coefficient is negative.

In the FE model, the AMI coefficient is statistically significant in reducing residential electricity use at the alpha = 0.05 level (p-value = 0.016; 95% CI: -0.0164 to -0.00168). Holding all else constant, each percentage increase in AMI penetration for residential utility customers results in a -0.006% change in expected average residential electricity use. We reject the null hypothesis that utility customers with AMI have the same electricity use as those without.

The average AMI penetration for utility operations in this dataset is 10.8% of residential customers. If each percentage increase in AMI penetration decreases average utility consumption by 0.009%, then the electricity reduction from 10.8% AMI penetration is about 0.097%. In a meta-review of studies providing real-time information feedback, such as that from AMI, electricity reductions ranged from 0.5% to 18% from (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). This study finds a smaller impact from information feedback, almost a magnitude lower than the lower bound from the meta-review. AMI installations are ongoing. It may be that even though AMI meters are installed, consumers may not have access to information feedback. In 2013, 37.8% of all meters were AMI enabled and only 22.5% of all metered households had access to daily digital access (U.S. EIA, 2015b). There may be a lack of urgency in implementing information feedback programs as this additional benefit from AMI may not be the core motivation or initial focus. Many utilities are installing AMI and smart grid infrastructure for the cost savings they afford (Allcott, 2011). If a portion of installed AMI meters do not yet provide information feedback to residential consumers, the full consumer side benefits will not be realized until information feedback programs are fully instituted. Likewise, if information feedback is not readily accessible, such as if consumers just go to a website to retrieve their daily usage, the information may not be as impactful and the results from these programs may not be as pronounced. If either of these arise, then the electricity reductions from AMI installations will be lower than the full potential savings from these technologies.

3.5.1-2 Time Response Programs

In both the OLS and FE model, the coefficient for time response programs is positive and of the opposite sign than expected. In the OLS model, the coefficient is positive and significant, suggesting that higher time response program participation increases average residential electricity use in a utility. Once within utility time-invariant effects are controlled by the FE model, the coefficient is still positive, suggesting that each percentage increase in time response program penetration increases residential energy use by 0.017%. However, this coefficient is no longer significant in the FE model.

Because the result is not significant, we fail to reject the null hypothesis that the average residential electricity use of utilities with more time response program participants and energy pricing information is the same as the average residential electricity use of utilities without such programs, controlling for weather, socio-demographic factors, suburbia, and year time trends.

Few utilities in the dataset had high penetration of time response programs in their residential programs. On average, less than one percent (0.91%) of all residential customers in this dataset from 2009 to 2013 were enrolled in time response programs. Of the utilities with time response programs, only 0.54% had 50% or more of all residential customers enrolled in time response programs. This question should be revisited with more detailed data on time response programs.

3.5.2 Environmental Information

In the OLS model, the coefficient for the per capita LEED buildings is negative and highly significant. According to the OLS model, as the per capita LEED buildings increase in a state, the average utility residential electricity use decreases, holding all else constant. Once utility level characteristics are accounted for in the fixed effects model, the coefficient is no longer significant. As the number of LEED certified buildings per capita increase in a state, the FE model finds no significant impact on average utility residential electricity use. It appears that the greater availability of building energy information from higher prevalence of LEED certified buildings in a state have no significant impact on residential electricity use.

3.5.3 Commute Time

Communities with higher work commutes have higher average residential electricity use, holding all else constant. However, once we control for utility level characteristics, we find that as commute times increase, average residential electricity use in a utility actually decreases, all else constant. As the average work commute increases by one hour in a utility, expected average household electricity use decreases by 2.3%, holding all other variables constant. However, this result is not significant. There is only weak support that household electricity use decreases as work commutes increase in time, which is opposite of the expected direction. It may be that longer work commutes mean less time for not only making better energy decisions, but also less time for all other activities, such as purchasing new gadgets and using technologies in the home. However, the current data are inconclusive on the impact of work commutes on residential energy use. The hypothesis that utilities in communities with higher commute times have increased average household electricity use, controlling for weather, socio-demographics, suburbia, and year time trends, is rejected.

3.5.4 Control Variables

3.5.4-1 Income Elasticity

In the fixed effects model, estimated income elasticity is 0.277 and highly significant. Holding all else equal, for each percentage increase in average income, expected annual residential electricity use in a utility increases by 0.277%. As expected, households use more electricity as income increases. This value is similar to the results of Espey and Espey's meta-analysis of residential electricity demand, where they find a mean income elasticity of 0.28 (2004).

3.5.4-2 Price Elasticity

In the FE model, the price elasticity is -0.176 and highly significant. This suggests that holding all else constant, for each percentage increase in average electricity price, expected annual residential electricity demand decreases by 0.176%. This price elasticity estimate is similar to the upper bound of -0.15 in Taylor's survey of residential short-run price elasticity for electricity demand of studies using average price. It is also similar to Bohi and Zimmerman's consensus estimate of -0.20 in their review of 18 studies examining periods between 1957-1980 (Bohi & Zimmerman, 1984; Taylor, 1975). It is lower than Espey and Espey's mean -0.35 for short-term price elasticity of residential electricity demand in their meta-analysis of 30 studies published from 1973-2000 (Espey & Espey, 2004). This study finds a largely similar price elasticity to the upper bound of Taylor's range and Bohi's consensus estimate, which included the energy crises of the 1970s. However, this study finds consumers are less elastic than suggested by Espey and Espey's mean of -0.35 from their meta-analysis, which included studies examining more recently time periods up to 2000. Espey and Espey find residential consumers were more inelastic in the short-run during the 1970s energy crises (Espey & Espey, 2004). It may be that consumers became more inelastic during 2009-2013 as a response to the Great Recession.

3.5.4-4 Suburbia Variables

A one percent increase in owner occupants in the population served results in a 0.49% decrease in expected annual household electricity use, holding all other variables constant. This is highly significant and suggests that owner occupants may implement more energy efficiency and energy conservation measures than renters. This may be due to their greater ability to alter the home and its energy efficiency since they own it. The impact of the percentage of detached houses in a utility's service area does not significantly impact expected average residential electricity use in either the OLS or FE model.

The OLS model suggests that average residential electricity use in a utility increases when the residential building stock is newer, all else equal. Once within group effects are considered, the FE model finds the average residential energy consumption in a utility decreases by 0.42% as the median year built for residential building stock increases by one year. This result is highly significant. As newer residential buildings are built, average residential electricity use in the utility decreases, all else constant. This suggests that newer residential buildings are more energy efficient than older buildings and that the energy savings from their improved energy efficiency can be seen at the utility level.

The coefficient on the percentage of the working population using public transportation is significant at the alpha = 0.05 level. Holding all else constant, a one percent increase in the working population taking public transportation leads to an expected increase in annual household electricity use of 0.8%. This may be due to an indirect rebound effect, where individuals using public transportation increase their energy use at home. Householders may feel justified in applying the economic savings from using public transportation to increase household comfort, such as more heating and cooling, or to increase enjoyment, like purchasing or using more electronic devices. Since income is included in these models, these results already control for income.

To explore the potential rebound effect impact, further analysis was conducted to estimate the rebound effect from an approximate 0.8% increase in average household electricity use in households using public transportation for work. The minimum and maximum fuel efficiency between 2009-2013, as reported by the Bureau of Transportation Statistics, was used in the calculation (U.S. Department of Transportation, 2015). The minimum and maximum travel times for the dataset (9.1 and 42.1 minutes respectively), were used and speeds of 25 mph and 70 mph were assumed. See Table 3-3 for values used in the rebound effect calculation.

Table 3-3. Values Used in Rebound Effect Calculation

	Mean	Min	Max
Average Fuel Efficiency[1] (mpg)		17.1	37.1
Travel time (minutes)	22.25	9.1	42.1
Speed (mph)		25	70
Energy Conversions			
Ave Energy Content of Gasoline[2]	114,500 BTU/gal		
1 kWh	3412 BTU		

[1] U.S. Department of Transportation, 2015
[2] U.S. Environmental Protection Agency, 1995

Using the analysis results and assumptions above, a range of rebound effect estimates were obtained from varied assumptions of commute time, speed, fuel efficiency, household electricity use. It is assumed that only one working householder using public transportation yields the increased electricity use. This provides an upper bound estimate of the impact, as the rebound effect will decrease as more householders use public transportation for the same estimated impact. From these results, the estimated rebound effect from public transportation usage varies from 0.03% to 19.5%. Results for rebound effect calculations are presented in Table 3-4, assuming one working and commuting via public transportation, respectively.

Table 3-4. Estimated Rebound Effect from Public Transportation, One Worker/Household

Household Electricity Use		Increase (kWh)	Min Trip		Max Trip	
			Gas Use - Increase (kWh)	Rebound Effect	Gas Use- Increase (kWh)	Rebound Effect
Min	1,667	13.4	1,564.28	0.85%	44,326	0.03%
Ave	11,956	95.9	1,481.76	6.08%	44,243	0.22%
Max	38,380	307.8	1,269.84	19.51%	44,031	0.69%

The estimated household electricity impact from a one percent increase of public transportation use by workers, when constrained to examining average household electricity use and assuming one working householder using public transportation, yields an approximate 0.22 – 6.08% rebound effect. This implies that, on average, about 94% or more of the energy savings from using public transportation versus private transport are still retained. Therefore, though the results suggest householders using public transportation for work commutes increase their household electricity use by about 0.8%, this increase is slight. Public transportation is an effective method to reduce transportation energy use even considering this potential rebound effect.

3.5.4-3 Impact of Age

Though the percentage of the population over 65 did not significantly impact residential energy use, the percentage of youth was significant at alpha = 0.05. For each percentage increase in the population under 18, expected annual household electricity use in a utility increases by 0.82%, holding all else constant. Utilities in areas with a higher youth population have higher expected average household electricity use, all else constant.

3.5.5 Weather

Lastly, weather is commonly included in models of residential energy behavior. Both CDD and HDD were examined in this study. Holding all else constant, for each additional thousand CDD per year, expected annual residential electricity use in a utility increases by about 10%. For each additional thousand HDD per year, expected annual residential electricity use in a utility increases by about 4.9%, holding all else constant. This result suggests that an additional CDD increases household electricity demand more than a HDD. This is not unexpected as air conditioning is electric powered and heating can be either electric or natural gas powered.

3.6 Conclusions and Policy Impacts

This study uses utility level residential data to explore the impacts of advanced metering infrastructure and time response programs on residential electricity demand. Few studies have examined how these smart grid components impact residential energy use across utilities.

Utility smart grid is still developing and in early stages of implementation. Only 10.8% of utility operations in the dataset have AMI available. Of those with these programs, only 10.7% had them available to 50% or more of their residential customers. Within a utility operation, each percentage increase in residential AMI penetration significantly reduces average utility residential electricity use by 0.009%, holding all else constant. Even with 100% AMI penetration within a utility, the current energy savings realized by AMI in this sample would reduce average residential electricity use by 0.9%.

At these early stages of smart grid implementation, it appears that the full possible benefits of information feedback to residential consumers is not currently realized. Even though AMI installations have increased over the years, smart grid information feedback to residential consumers may not be at maximal effectiveness. This may be due to several issues. First, even though smart grid infrastructure has been installed, it may be that smart grid information feedback has not been fully implemented in all existing smart grids. Second, smart grid information feedback may not be readily accessible and consumers may not be viewing it. Third, the information provided by smart grid may not be optimally designed to impact consumer energy behavior. If immediate smart grid effects on residential energy use are desired, more efforts need to support understanding and implementing effective information feedback.

Smart grid policies can support data gathering and research to inform future smart grid success. Policies can request data from electric utilities regarding the types of information feedback provided by their smart grids, the percentage of their customers that access this information, and how households participate in these information programs (opt in or opt out). With this information, determining why some smart grids are more effective than others in modulating residential electricity demand will be easier. Policies can also support additional research to support smart grid success. More research is needed to determine the best ways to display information feedback to consumers. Research should also explore how consumers respond to different access methods and determine which are the most effective methods.

Future researchers should revisit the impact of AMI programs on average household utility consumption when smart grid penetration increase and information feedback is fully functional. Smart grid impacts may be more visible across utilities as they become more prevalent, information feedback is more uniformly implemented, and utilities gain additional expertise with these new technologies. Though smart grid development may be initially focused on updating the electrical infrastructure to obtain real-time information feedback to the utility, real-time information feedback to consumers brings added benefits by lessening residential energy demand. Understanding smart grid impacts on utility demand is important as we modernize our electrical grid. Only then will we fully grasp all the opportunities a smarter electrical grid can provide.

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CHAPTER 4. PROJECTIONS OF A NATIONAL RESIDENTIAL SMART GRID

4.1 Introduction

The next generation electrical grid, the smart grid, is being rapidly deployed throughout the world. Smart grids introduce two-way communications and computational intelligence into the electrical grid to achieve a secure, resilience, and sustainable system (Fang, Misra, Xue, & Yang, 2012; Farhangi, 2010; Sintov & Schultz, 2015). Automatic metering infrastructure (AMI) technology is central to smart grids by enabling two-way communications between consumers and utilities (Sintov & Schultz, 2015). Smart grid introduces a new paradigm of active distribution where consumers become active players (Gangale, Mengolini, & Onyeji, 2013). The importance of consumer adoption, engagement, and trust in smart grids are considered essential for successful roll-out of the technology (Sintov & Schultz, 2015; Xenias et al., 2015). This reliance on consumer engagement is considered a barrier by some experts (Xenias et al., 2015). Despite this and other concerns like cyber security (Wang & Lu, 2013), experts consider the evolution to a smarter grid necessary (Farhangi, 2010; Xenias et al., 2015).

The traditional electrical grid faces many issues. The electrical grid is unidirectional with clear demarcations between generation, transmission, and distribution subsystems (Farhangi, 2010). Electrical generation efficiency has not increased for more than half a century and transmission cables are still largely 1950s technology facing significant electrical transmission losses (Brown, 2007). About only one third of fuel is converted to electricity, with another 8% lost along transmission lines. The traditional system is engineered to meet maximum anticipated peak demand. About 20% of generation capacity is for this purpose alone and only used about 5% of the time. The traditional electrical system lacks real-time control. Even in North

America, with one of the world's most advanced electrical systems, more than 75% of the distribution system lacks information and communication systems. Meanwhile, increased electricity demand and decreased electrical infrastructure investment compromises system stability (Farhangi, 2010).

Smart grid addresses many of these issues. Not only does it accommodate many generation options, its real-time communications allow rapid identification of problems. System intelligence allows more rapid resolution or mitigation of problems (Fang et al., 2012; Farhangi, 2010). Though its predicted benefits are many, smart grid is in early developmental stages, where new technologies and methods are emerging, competing, and demonstrating effectiveness (Erol-Kantarci & Mouftah, 2015; Fang et al., 2012).

Smart grid progress relies not only on technological, regulatory, and legislative innovations. It also requires consumer engagement and acceptance (Colak, Fulli, Sagiroglu, Yesilbudak, & Covrig, 2015). Experts believe smart grid data and privacy must be assured to gain consumers trust (Xenias et al., 2015). As smart grid is more ubiquitous, larger in size, and more automated, it faces increasing security challenges (Yan, Qian, Sharif, & Tipper, 2013). The heterogeneous smart grid communication network, with varied devices, architecture, and capabilities, make uniform deployment of security approaches across the grid unlikely (Wang & Lu, 2013). Instead, security solutions designed for specific network applications will be necessary (Wang & Lu, 2013), making smart grid and smart meter security a challenging area of research (Sharma & Mohan Saini, 2015; Wang & Lu, 2013).

Smart grid deployment is not uniform. Its implementation is dependent on factors such as state policies, utility technological experience, and regulatory incentives (U. S. Department of Energy, 2014). It is difficult to extrapolate lessons learned from individual smart grid programs to understand the implications of a national residential smart grid. This chapter explores the energy impacts from effective consumer engagement with smart grids through policy modeling.

This chapter models the impacts of price elasticity and rebound effect changes that approximate the consumer engagement programs supported by national residential smart grid. It uses the National Energy Modeling System (NEMS) to project economy wide impacts. Smart grid technology is still undergoing research and development. It is difficult to determine the final form and cost of a national smart grid. This chapter makes no assumptions regarding the technologies employed in such a scenario. To do so in an area with new and emerging technologies requires prophetic powers of which this author does not possess. Instead, it focuses on examining the energy and economy wide impacts from price elasticity and rebound effect changes that might be expected from smart grid. First, pertinent literature and methodology are described. Next, the results are detailed and discussed, followed by the conclusions.

4.2 Literature Review and Background

Much research has been conducted to understand consumer energy behavior, especially the impact of additional information on behavior. Still, research on how to best present information to consumers and strategies for increased consumer engagement are lacking (Gangale et al., 2013). Consumer engagement is essential to the success of smart grid (Sintov & Schultz, 2015; Xenias et al., 2015). There is a growing need for behavioral research in the energy sector to inform smart grid development through program evaluations and readily available results (Sintov & Schultz, 2015).

Thus far, we know that there are many ways to elicit consumer behavior change through information provision. Consumer decisions can be biased or "anchored" by previously presented material (Arana & Leon, 2008; Bond, Carlson, Meloy, Russo, & Tanner, 2007). Emotional cues can increase attention and processing speed (Dolan, 2002). Emotional intensity and anchoring have a U-shaped relationship, where anchoring effects impact consumer preferences more when emotional intensity are at extremes (Arana & Leon, 2008). Social norms and peer influence can affect energy behavior and recycling (Abbott, Nandeibam, & O'Shea, 2013; Yue, Long, & Chen, 2013). Consumer behavioral change is greater when information is from known people and trusted information sources (Kua & Wong, 2012; McMichael & Shipworth, 2013). The likelihood of adopting energy efficiency measures increases by up to four times when consumers receive information from personal contacts (McMichael & Shipworth, 2013). Consumers are more likely to overweigh information from high expertise and high correlation sources (Luan, Sorkin, & Itzkowitz, 2004). All of these consumer behavior findings can be implemented in the smart grids by designing the information content and delivery style.

However, few researchers have examined how to best present this information, even many projects have explored information provision to consumers (Gangale et al., 2013). More studies on how to best present information are required. Several studies on the impact of information on residential energy use are discussed below.

Smart grid technologies provide a structural change, one that can increase consumer price elasticity of electricity demand (Allcott, 2011a). Price elasticity increases from more frequent consumption and pricing information, like that which smart grid programs can provide (Jessoe & Rapson, 2014; Wolak, 2011). Few papers estimate the price elasticity change from providing more information. In one of these, Gaudin estimates the price elasticity impacts from additional pricing information on water bills from 383 utilities. He finds a 30% or more decrease in price elasticity (-0.36 for areas without and -0.51 for areas with additional price information) when additional price information is added to bills (2006). Just providing pricing information to consumers more frequently, as smart grid technologies are capable of doing, can make consumer demand more elastic. At high prices, higher price elasticity decreases demand for the energy service. At lower prices, higher price elasticity increases energy service demand.

Residential consumers decrease electricity use when provided with additional consumption information. Empirical studies on consumption feedback to residential households finds it decreases subsequent use by as much as 5-10% (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Matsukawa, 2004; Seligman & Darley, 1977). Consumers are also influenced by others' decisions (Kasanen & Lakshmanan, 1989). Studies on providing peer consumption of feedback finds sustained electricity decreases of 1.2-2.1% (Allcott, 2011b; Ayres, Raseman, & Shih, 2013). These findings show that consumers decrease electricity use when additional consumption information is provided on their electricity consumption.

Decreased electricity use with more consumption information suggests consumers change their behavior to save energy. This may arise due to consumers changing their price elasticity, similar to their response to additional pricing information. It may also be due to consumers decreasing existing rebound effects within their household by decreasing non-essential electricity use. The rebound effect can be mathematically expressed as the percentage difference in actual and calculated energy consumption after energy efficiency implementation (Druckman, Chitnis, Sorrell, & Jackson, 2011; Freire-González, 2011; Haas & Biermayr, 2000). Theoretically, the rebound effect is attributed to only changes in consumer energy behavior after efficiency implementation. Though the price elasticity is closely related to the rebound effect and is used many times to empirically estimate it (Berkhout, Muskens, & Velthuijsen, 2000), the rebound effect is distinct. The rebound effect is a function of not only price elasticity of the energy service in question, but also its energy intensity as compared to other substitutes and complements (Berkhout et al., 2000). Therefore, change in energy consumption from altered rebound effect need not be identical to changes from altered price elasticity and the rebound effect may be modulated by additional consumption information.

4.2.1 NEMS Background

NEMS is a modeling program used by the Energy Information Administration (EIA) to project the energy, economic, environmental, and security impacts of U.S. energy policies and market changes (U.S. EIA, 2009). The program uses a general equilibrium model to project U.S. energy supply and demand for each year up to 2040 (U.S. EIA, 2014b). NEMS is updated annually with recent energy policies. Though used mainly to generate EIA's Annual Energy Outlook, NEMS is also used for policy analyses for the Administration, Congress, and governmental agencies on request (U.S. EIA, 2009). As such, NEMS has significant policy impacts.

NEMS uses a modular approach with various supply, demand, and conversion modules. Each is relatively self-contained. An integrating module achieves a general market equilibrium among all modules. Modules share information such as price, quantity, economic activity, capital expenditure, and international energy supply curves (U.S. EIA, 2014a). See Figure 4-1 for a figure of the various NEMS modules and their relationships.

This chapter focuses on the residential sector and the NEMS Residential Demand Module (RDM). Using NEMS inputs of energy prices and macroeconomic indicators, the RDM generates residential energy consumption by end-use service, fuel type, and Census Division. It then computes equilibrium energy prices and quantities. It also outputs information needed in the NEMS integration process (U.S. EIA, 2014b).

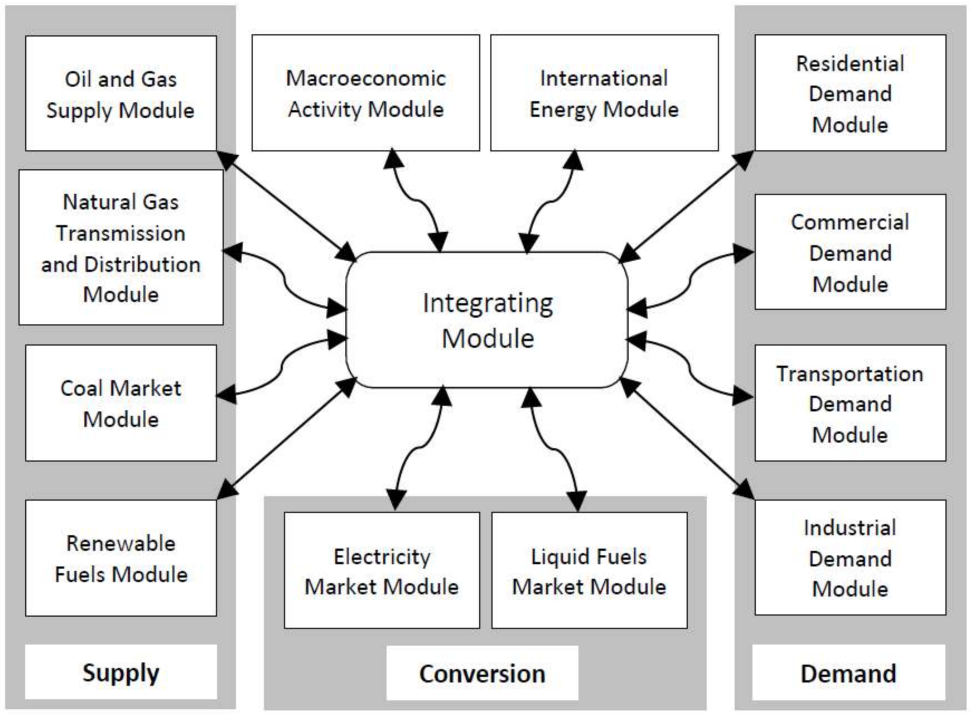

Figure 4-1. NEMS Model Structure and Flow (U.S. EIA, 2014a)

In the residential sector, NEMS employs changes to short-term price elasticity of electricity demand to simulate successful smart grid deployment. Short run price elasticity focuses on consumption changes, while long run price elasticity also includes changes in equipment stock (Gillingham, Newell, & Palmer, 2009). In the residential sector, the short-term price elasticity of demand decreases from -0.15 to -0.30 from 2010 onwards for electricity (U.S. Energy Information Administration, 2015). Bohi and Zimmerman review 18 publications with estimates of short-term price elasticity for residential electricity demand. From this review, they arrive at a consensus estimate of -0.20 for short-term price elasticity (Bohi & Zimmerman, 1984). This estimate is higher than the -0.15 value assumed by NEMS under status quo situations without smart grid. Espey and Espey examine 30 studies published from 1973-2000 for estimates of short-term price elasticity of residential electricity demand. Values range from -2.1 to -0.004 with a mean of -0.35 and a median of -0.28 (Espey & Espey, 2004). The mean value of -0.35 is higher than the assumed short-run price elasticity assumed within NEMS of -0.30 to model smart grid implementation. Price elasticity varies for geographic regions and methods employed, but it is likely that the short-run price elasticity of electricity demand without smart grid implementation is near or higher than short-run price elasticity of electricity of -0.30 assumed by NEMS with residential smart grid.

The NEMS RDM applies price elasticity and efficiency rebound effects to three end-uses: heating, cooling, and lighting (U.S. Energy Information Administration, 2015). For heating and cooling end-uses, the rebound effect is calculated by the following general equation (U.S. Energy Information Administration, 2014b):

$$RB_{y,eg,b,r} = (WTEQCEFF_{y,eg,b,r} * RTBASEFF_{baseyr,eg})^{\alpha_1}$$

where $RB_{y,eg,b,r}$ is the rebound effect, $WTEQCEFF_{y,eg,b,r}$ is the equipment efficiency weighted by market share of the specific equipment from technology choice, and $RTBASEFF_{baseyr,eg}$ is the efficiency of the weighted average of units from existing base year stock, α_1 is the short term price elasticity of energy demand (rebound effect elasticity) valued at -0.15, *y* is the year, *eg* is the equipment class, *b* is the housing type, and *r* is the Census Division.

There are three equations for rebound effect: surviving equipment (RBA), replacement equipment (RBR), and new equipment (RBN) (U.S. EIA, 2014b). Rebound effect values vary by equipment, housing type, and census division. The NEMS definition of rebound effect is different than the usual definition of rebound effect. For example, a rebound effect of 3% is given a value of 1.03 in NEMS. The magnitude of rebound effect for equipment within NEMS is low compared to some estimates of rebound effect. Table 4-1 and 4-2 display the average rebound effect values for all census divisions by equipment type for heating and cooling end uses, respectively, in 2015 within the NEMS 2015 version that is used here. Rebound effects used in NEMS are presented as percentages.

Table 4-1. Average Heating Rebound Effects in 2015

Equipment Type	Surviving Equipment	Replacement Equipment	New Equipment
Electric Radiator	0%	0%	0%
Electric Heat Pump	5.25%	4.04%	4.02%
Natural Gas Furnace	1.47%	1.69%	1.54%
Natural Gas Radiator	0.63%	0.57%	0.56%
Kerosene Furnace	0.93%	0.78%	0.75%
LPG Furnace	1.97%	2.13%	1.63%
Distillate Fuel Oil Furnace	1.50%	1.08%	0.93%
Distillate Fuel Oil Radiator	0.79%	0.81%	0.80%
Wood Heat	-7.27%	-8.71%	-8.71%
Geothermal Heat Pump	4.98%	1.00%	1.00%
Natural Gas Heat Pump	0%	0%	0%

Table 4-2. Average Cooling Rebound Effects in 2015

Equipment Type	Surviving Equipment	Replacement Equipment	New Equipment
Room Air Conditioner	1.96%	1.96%	1.96%
Central Air Conditioner	2.32%	2.68%	2.67%
Electric Heat Pump	2.96%	2.41%	2.43%
Geothermal Heat Pump	2.78%	2.19%	2.19%
Natural Gas Heat Pump	0%	0%	0%

4.3 Research Question

This study examines the impact of rebound effect and price elasticity of electricity changes that might arise from a national residential smart grid. It asks: What are the impacts of rebound effect and price elasticity of electricity changes in the residential sector at varying levels?

4.4 Methodology

The NEMS modeling plan focuses on source code alterations. A similar methodology was used in the NEMS modeling for Making Homes Part of the Climate Solution (Wang, Wang, Brown, & Jackson, 2011).

First, the residential sector module and source code were both examined to determine possible levers. Modifiable levers within the residential sector include: price elasticity, rebound effect, discount rate, equipment efficiencies, and implementation dates for efficient technologies (U.S. EIA, 2014). Price elasticity and rebound effect changes, the most likely levers to model a smart grid program, cannot be altered through existing input files within NEMS. They can only be modified through source code changes.

The value for electricity price elasticity was first modified to reflect literature findings. Two values for short-run price elasticity are used, -0.24 and -0.35. The estimate from Bohi and Zimmerman is averaged with the median estimate from Espey and Espey to arrive at -0.24. Espey and Espey's mean value of -0.35 is also used as a sensitivity (Bohi & Zimmerman, 1984; Espey & Espey, 2004). Since Gaudin found a 30% increase in price elasticity with additional pricing information (2006), the short-run price elasticity of electricity is next increased by 30% to reflect smart grid implementation. The values assumed for short-run price elasticity after smart grid implementation are listed in Table 4-3.

Table 4-3. Assumed Values for Short-run Price Elasticity of Electricity

	Before Smart Grid Implementation	After Smart Grid Implementation
Value 1	-0.24	-0.31
Value 2	-0.35	-0.46

To implement the price elasticity changes, all source code values for short-term price elasticity for electricity (denoted by "alpha") were changed from the reference case values to -0.31 or -0.46. Price elasticity for electricity for the following uses were changed:

- heating,
- cooling,
- water heating,
- dryers,
- lighting,
- miscellaneous electrical devices
- electric motors,
- and electric heating elements.

NEMS rebound effects values for heating and cooling end uses are altered. Three sensitivities for rebound effect are implemented, 100%, 90%, and 65% of NEMS reference case rebound effect formula. The rebound effect was attenuated by each percentage in the source code if the rebound effect was positive (i.e. RBA, RBR, and RBN all greater than 1).

An additional six scenarios were also tested with increased the NEMS reference case rebound effects formulas for heating and cooling end-uses. Multipliers were calculated to increase the rebound effects to an average of 42% for 2015 NEMS reference case values for heating and cooling rebound effects by equipment type. This value is based on the average rebound effect of 42% found in meta-analysis of residential rebound effect in Chapter 2. Rebound effect multipliers are 1.42 for heating end-uses and 1.39 for cooling end-uses based on reference case 2015 values for heating and cooling rebound effects averaged over equipment types. In total, twelve different scenarios combining price elasticity and rebound effect changes were examined.

The NEMS 2015 reference case currently includes smart grid. In it, the short-run price elasticity of electricity increased from -0.15 to -0.30 for years 2009 and later to model the impact of stimulus funding for smart grid. To better estimate the total projected savings from national smart grid, the six scenarios are compared to a scenario where short-run price elasticity of electricity remains at a constant -0.15 (no smart grid assumed) throughout the projection period. This scenario with a constant -0.15 short run price elasticity of electricity will be called the revised NEMS 2015 reference case or the revised reference case. Likewise, another revised NEMS 2015 reference case scenario with inflated rebound effect was also created to compare with the high rebound effect scenarios. This version will be called the revised NEMS 2015 reference case with high rebound effects.

The six different scenarios relying on reference case rebound effects were compared with the revised reference case, where no smart grid is assumed. There are three scenarios per assumed price elasticity. As rebound effect decreases in the scenarios, they can be interpreted as increasingly effective smart grid programs through providing more effective information.

The six different scenarios relying on inflated rebound effects were compared with the revised reference case with high rebound effects. See Table 4-4 for scenario names and descriptions of short-term price elasticity of electricity and rebound effect changes.

Table 4-4. Scenario Names and Descriptions

Scenario Name	Short-term Price Elasticity of Electricity	Reduction of Rebound Effect (Heating & Cooling End Uses)	Rebound Effect Size
PE31	-0.31	0%	NEMS reference values
PE31RE90	-0.31	10%	NEMS reference values
PE31RE65	-0.31	35%	NEMS reference values
PE46	-0.46	0%	NEMS reference values
PE46RE90	-0.46	10%	NEMS reference values
PE46RE65	-0.46	35%	NEMS reference values
PE31REHI	-0.31	0%	Inflated values
PE31RE90REHI	-0.31	10%	Inflated values
PE31RE65REHI	-0.31	35%	Inflated values
PE46REHI	-0.46	0%	Inflated values
PE46RE90REHI	-0.46	10%	Inflated values
PE46RE65REHI	-0.46	35%	Inflated values

4.5 Results and Discussion

4.5.1 Total Energy Savings

All scenarios reduce overall total energy compared to the scenario without residential smart grid. Though there are fluctuations over time, the total energy savings over all sectors generally increases during the projection period for all scenarios. See Figure 4-2 for the yearly projected total energy savings over all sectors from 2016 through 2040 for scenarios with low assumed rebound effects. See Figure 4-3 for yearly projected energy savings for scenarios with high rebound effects. Each scenario is compared to the applicable revised reference case.

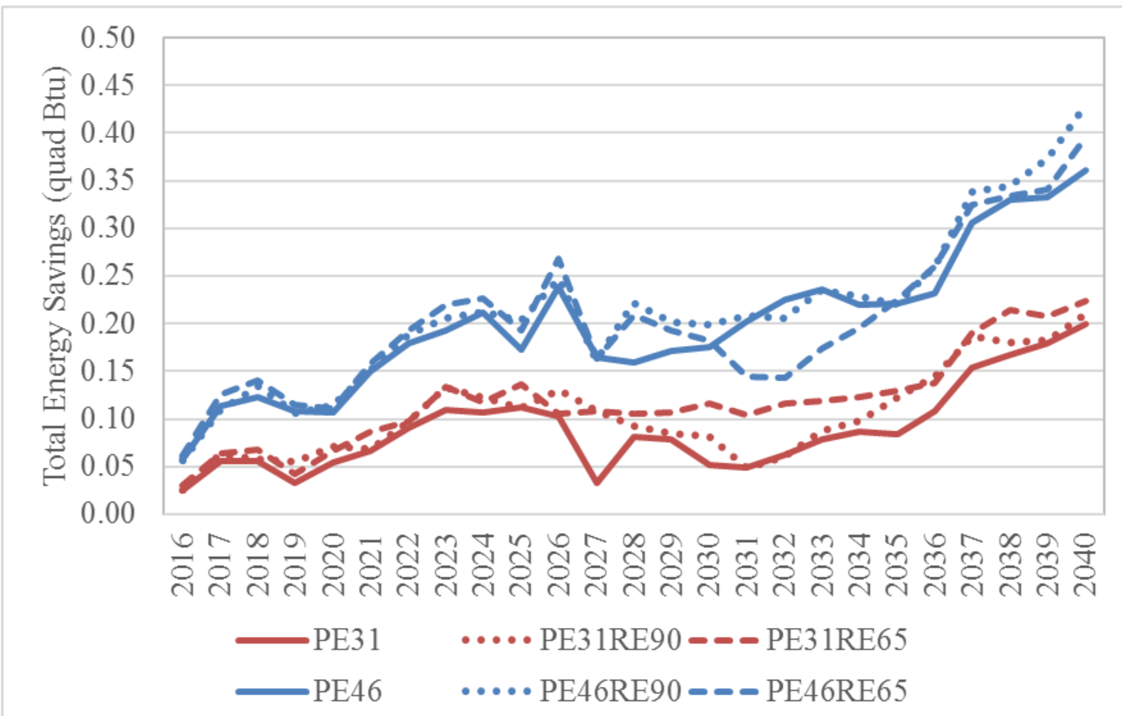

Figure 4-2. Total Energy Savings from Smart Grid Scenarios, All Sectors, Low Rebound

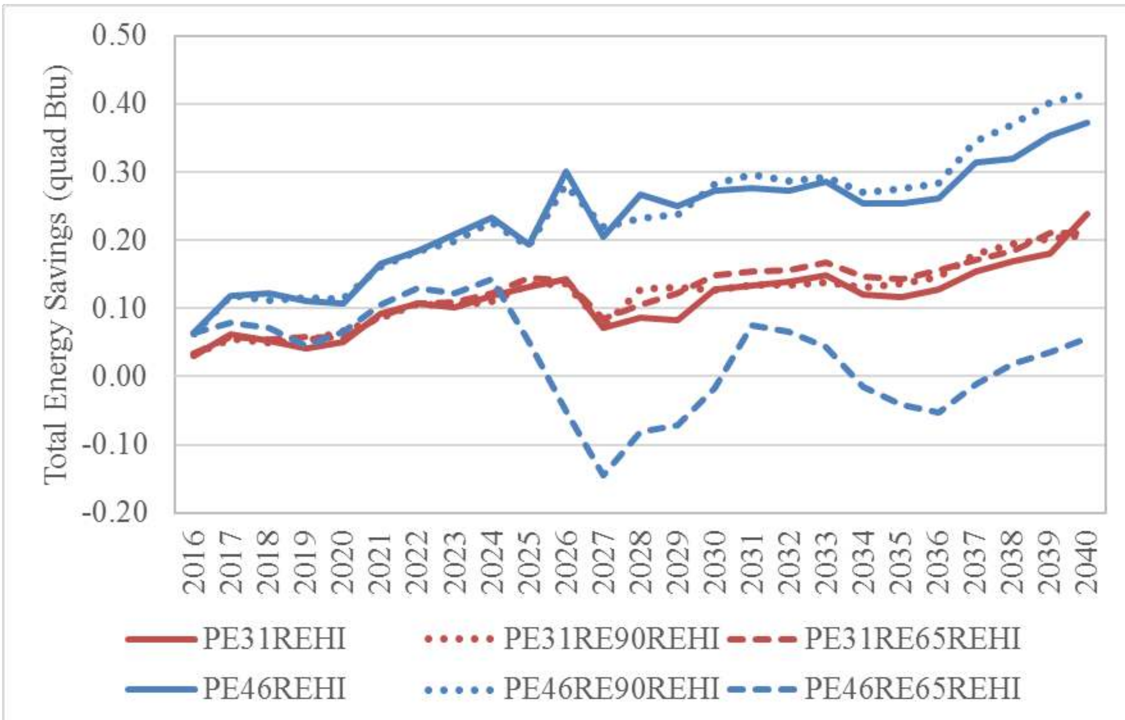

Figure 4-3. Total Energy Savings from Smart Grid Scenarios, All Sectors, High Rebound

The total projected energy savings across all sectors does not necessarily increase as the rebound effect decreases. In some cases, total energy savings across all sectors decreases as the rebound effect decreases, as in the case PE46RE65. This can be seen in Table 4-5. For example, PE46RE65 is projected to save 5,093 trillion Btu cumulatively from 2016 to 2040 across all sectors. However, PE46RE90, which reduces rebound effect to 90% of the reference case amount instead of 65%, is projected to save an additional 260 trillion Btu during the same time frame. Even though PE46RE65 models a scenario that reduces residential energy use more, it does not save more total energy across all sectors as a smart grid scenario assuming a higher rebound effect.

Generally, more total energy is saved in the residential sector than across all sectors. Cumulative total energy savings in the residential sector, ranging from 4,059 to 8,459 trillion Btu for low rebound effect assumptions and 4,257 to 8,403 trillion Btu for high rebound effect assumptions, generally exceed the overall savings across all sectors. Energy consumption changes in other sectors induced by a national residential smart grid program can substantially decrease realized energy savings from national residential smart grid, especially in the scenarios with low rebound effect assumptions. In these cases, 35-45% of residential sector energy savings are offset by energy demand changes in other sectors. With higher assumed rebound effects, less of the residential energy savings are offset by energy demand changes in other sectors. The amount offset ranges from -0.8% to 76.5%, with the majority ranging from 8.2%-19.1% reduction in residential sector savings from demand changes in other sectors. See Table 4-5 for the cumulative total energy savings in the residential sector and all sectors from a national residential smart grid program from 2016 to 2040 by scenario.

Table 4-5. Cumulative Total Energy Savings, 2016 to 2040, Residential and All Sectors

Scenario	**Total Energy, Residential Sector (Trillion Btu)**	**Total Energy, All Sectors (Trillion Btu)**	**Reduction in Residential Sector Savings from Other Sectors (%)**
PE31	4,059	2,224	45.2%
PE31RE90	4,319	2,619	39.4%
PE31RE65	4,702	2,950	37.3%
PE46	8,054	4,985	38.1%
PE46RE90	8,247	5,353	35.1%
PE46RE65	8,459	5,093	39.8%
PE31REHI	4,257	3,909	8.2%
PE31RE90REHI	4,496	3,761	16.3%
PE31RE65REHI	4,385	3,546	19.1%
PE46REHI	8,286	1,945	76.5%
PE46RE90REHI	8,403	7,395	12.0%
PE46RE65REHI	7,139	7,194	-0.8%

From these results, it is evident that rebound effect and price elasticity changes realize overall energy savings. However, there is significant variation in the projected energy savings depending on the scenario though. The expected demand changes cannot be predicted based on the degree at which rebound effects are attenuated. Lower rebound effects do not necessarily always lead to increased energy savings. However, it does appear that a scenario with lower price elasticity (-0.46 versus -0.31) realize greater energy savings than the same scenario but at a higher price elasticity.

The consumption changes in other sectors likely arise from projected lower energy prices in the smart grid scenarios. For the most part, residential smart grid scenarios decrease projected energy prices throughout most, if not all, of the projection period. This effect is most evident for electricity and natural gas prices. Projected average electricity prices and natural gas prices decrease for the majority of the projection period. Figures 4-3 and 4-4 shows projected changes in average electricity and natural gas price from 2016 to 2040 for the scenarios with low rebound effect assumptions.

The reduction in energy prices from reduced energy demand is called the "demand reduction induced price effect" (DRIPE) and has been suggested for energy efficiency investment. As consumers spend the resulting savings from reduced prices on more job-intensive goods and services, jobs are likely generated across the economy (Baer, Brown, & Kim, 2015). Smart grid programs reduce energy consumption much like energy efficiency technologies. It is not surprising, then, to see that DRIPE also applies to smart grid technologies. It is likely that smart grid may also stimulates some degree of job creation.

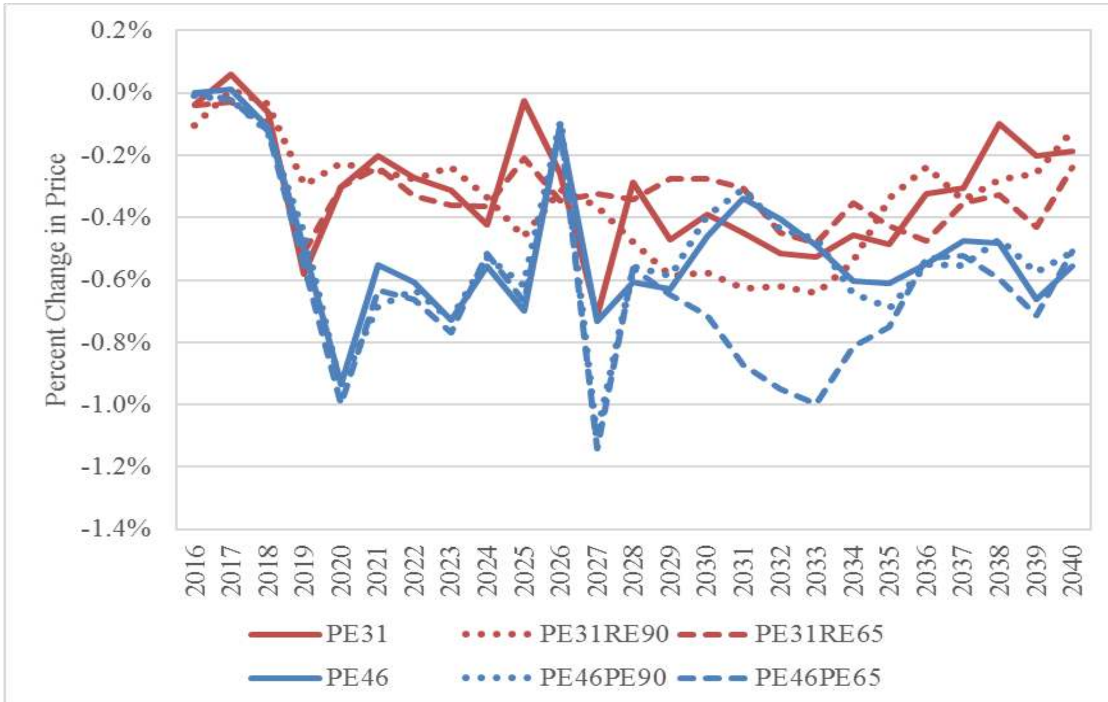

Figure 4-4. Average Electricity Price Changes from Low Rebound Effect Scenarios

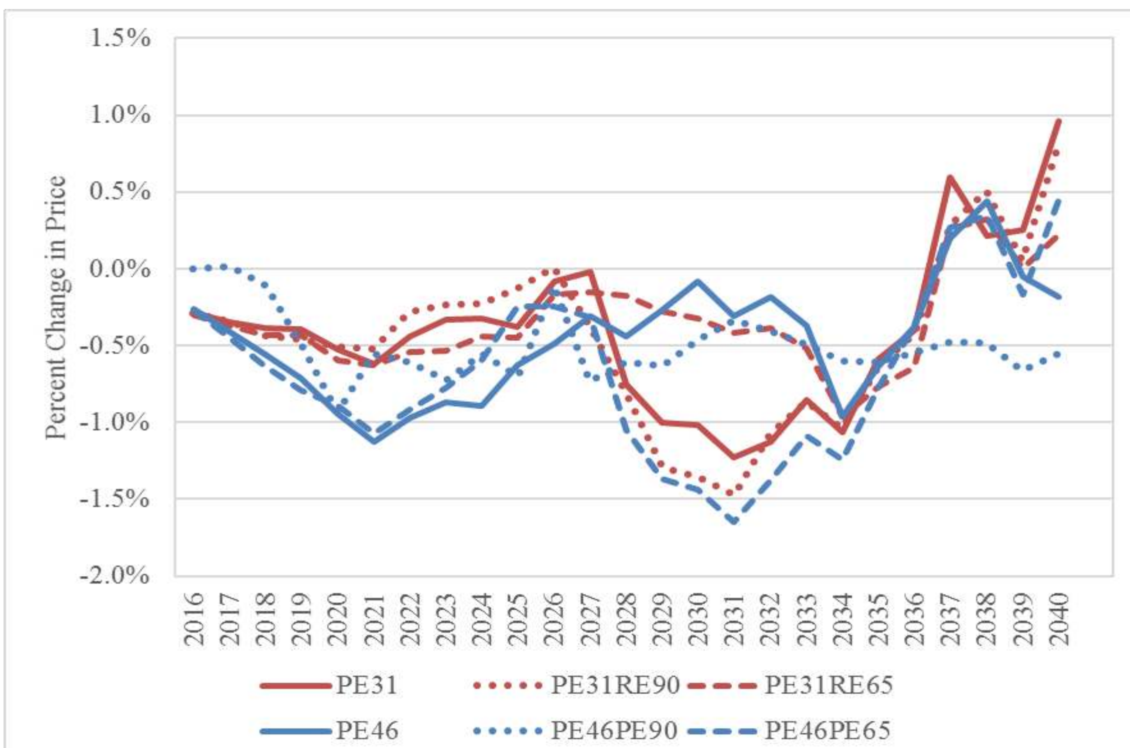

Figure 4-5. Average Natural Gas Price Changes from Low Rebound Effect Scenarios

Sectoral changes in energy demand are similar across scenarios with different short-run price elasticity scenarios for electricity. Even though the total energy savings are greater in scenarios with -0.46 price elasticity, similar trends are seen in both price elasticity scenarios regarding sectoral changes in energy use. The residential and electric power sectors are projected to reduce energy use. Energy savings in the residential sector are seen immediately, while energy savings in the electric power sector are more prominent beginning around 2030. Due to its dependency on long-lived equipment, the electric power sector may react more slowly to changes in demand as old technologies are retired and new facilities built. See Figure 4-5 and 4-6 for the projected annual total energy savings by sector for scenarios with price elasticity of -0.31 and -0.46, respectively, and low assumed rebound effects. See Appendix D for the projected sectoral total energy savings by year for scenarios with high rebound effects.

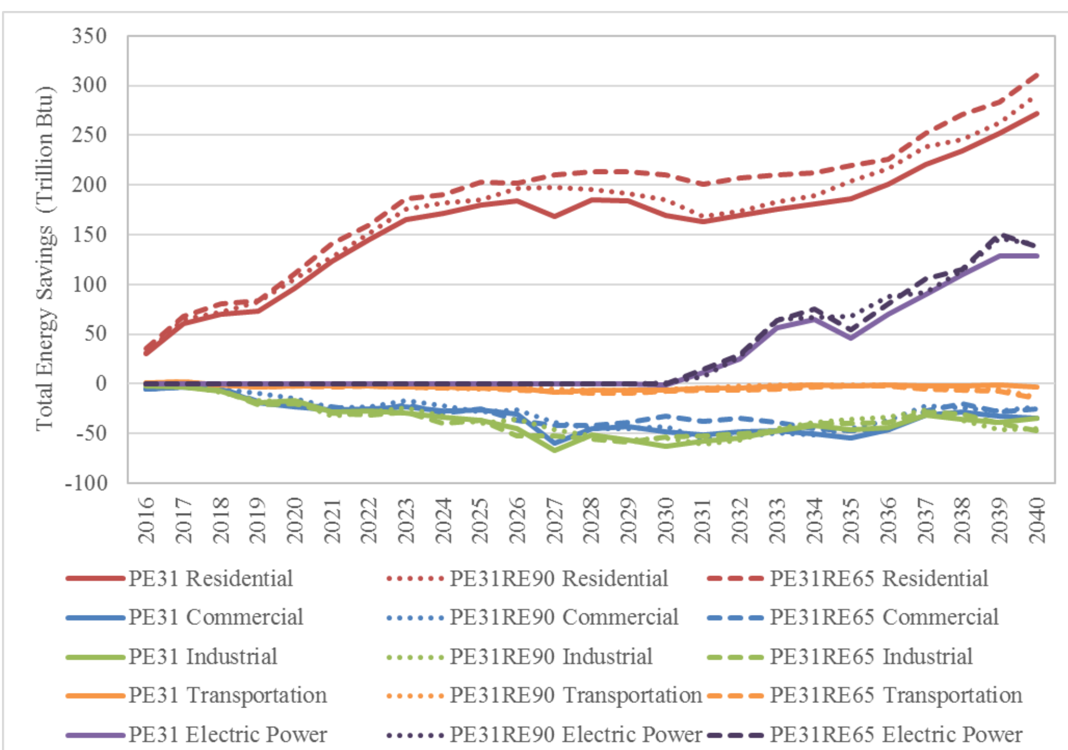

Figure 4-6. Total Energy Savings by Sector, Low Rebound Effect & Price Elasticity -0.31

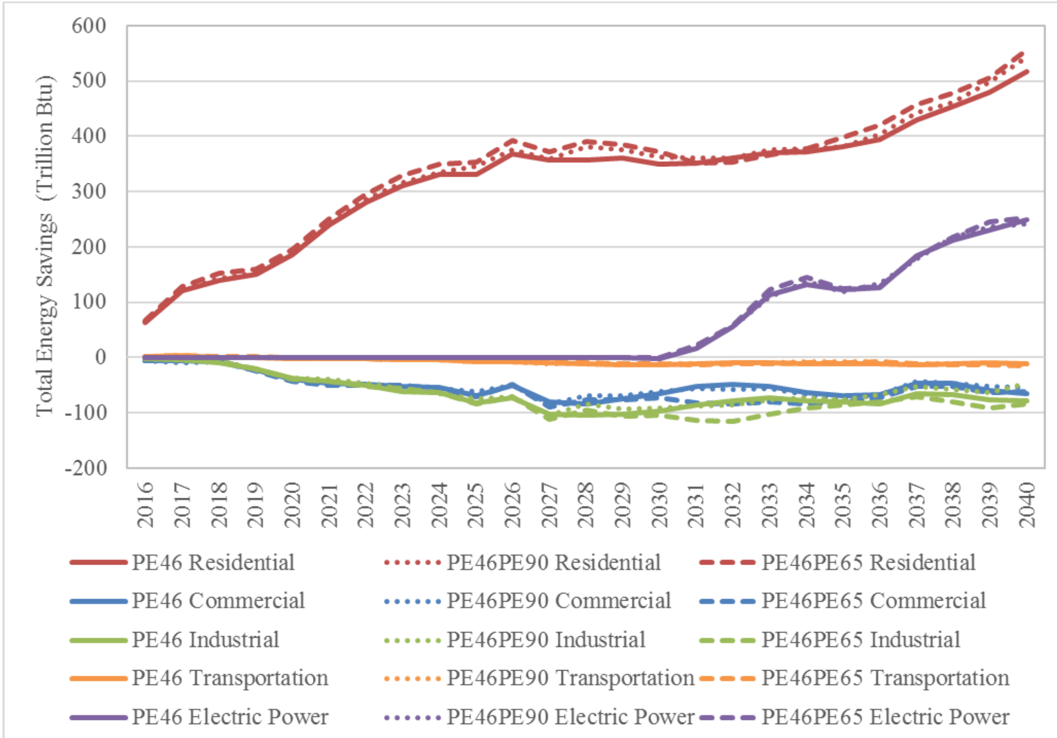

Figure 4-7. Total Energy Savings by Sector, Low Rebound Effects & Price Elasticity -0.46

Increased consumption is projected in the commercial, industrial, and transportation sectors. Most of the increased energy consumption is from the industrial and commercial sectors (See Figures 4-5 and 4-6). Electricity and natural gas change the most in price in the smart grid scenarios. Not only are industrial and commercial sectors more impacted by these energy price changes than the transportation sector, they also have more opportunities for fuel switching than the transportation sector.

However, increased consumption in these sectors are projected to be modest. Changes in total energy use in non-residential sectors are less than 1% absolute change. Excluding the electric power sector, change in total energy is below 0.5% absolute change. See Table 4-6 for percentage change in total energy use in 2040, where the impacts are most extreme, for scenarios with low rebound effects. See Appendix D for the table for scenarios with high rebound effects.

Table 4-6. Percentage Savings of Total Sector Energy Use in 2040, Low Rebound Effect*

Sector	REF15	PE31	PE31RE90	PE31RE65	PE46	PE46PE90	PE46PE65
Residential	1.25%	1.29%	1.37%	1.47%	2.44%	2.56%	2.62%
Commercial	-0.11%	-0.16%	-0.11%	-0.12%	-0.31%	-0.26%	-0.29%
Industrial	-0.06%	-0.09%	-0.12%	-0.13%	-0.21%	-0.12%	-0.22%
Transportation	-0.01%	-0.01%	-0.05%	-0.06%	-0.05%	-0.05%	-0.05%
Elec. Power	0.31%	0.31%	0.34%	0.33%	0.60%	0.58%	0.61%
TOTAL	0.20%	0.21%	0.20%	0.19%	0.37%	0.40%	0.34%

*If the percentages are negative, then total energy use increases and no energy is saved within that sector.

Total energy savings in the residential sector is projected to vary from 0.43% to 0.95% in 2020 and 1.3% to 2.7% in 2040 of total residential energy, depending on the scenario. The predicted reductions from smart grid information in the residential sector are similar to the energy reductions from NEMS projections of energy benchmarking for commercial buildings, which also address information access. Energy benchmarking is predicted to realize energy savings of 1.3-1.4% in 2020 and 2.2-2.4% in 2035 for the commercial sector (Cox, Brown, & Sun, 2013). In regards to past residential research on information provision, the level of energy reduction from the smart grid scenarios is in the modest range of the previous study findings which ranged from 0.5-18% (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). Reductions seen in 2040 are similar to the electricity decreases from providing peer comparisons in electricity feedback which realized sustained decreases of 1.2-2.1% (Allcott, 2011; Ayres, Raseman, & Shih, 2013). Many experimental studies on information feedback have realized much higher reductions in residential energy usage than projected here, suggesting the smart grid scenarios presented here are conservative.

Though the percentage of residential energy savings of total sector energy use may seem small, the avoided energy expenditures are significant. In 2013, energy expenditures in the U.S.

were 1.38 trillion dollars (U.S. EIA, 2016). Projected total energy savings across all examined scenarios range from 0.05% to 0.4% of all energy use. Assuming 2013 energy expenditure, this equates to $0.69 to $5.5 billion in avoided energy expenditure from these scenarios. If the percentage of energy savings in the residential sector can be maintained across all sectors, then additional avoided energy expenditures may be possible. Projected energy savings in the residential sector ranged from 1.25% to 2.64% across all scenarios. Assuming 2013 energy expenditure, this equates to a range of $17.3 to $36.4 billion of avoided energy expenditures. The energy savings projected from rebound effect and price elasticity changes that might arise from smart grid informational programs may seem small in light of total sector energy use, but they can result in substantial dollar savings.

4.5.2 Emissions and Other Impacts

These scenarios generally are projected to contribute to CO_2 emissions goals in 2030. The Clean Power Plan sets a goal of 32% reduction in the power sector CO_2 emissions from 2005 levels (US EPA, 2015). Additional CO_2 emissions reductions from these scenarios in 2030 range from -0.01% (PE31) to 0.74% (PE46RE65REHI). See Table 4-7 for the additional CO_2 reduction from each scenario in 2030 over 2005 levels in comparison to the associated revised reference scenario.

Table 4-7. Additional CO_2 Emissions Reduction in 2030 over 2005 levels (Percent)

	SCENARIO	
Scenario	**Low Rebound Effect**	**High Rebound Effect**
PE31RE65	0.05%	0.09%
PE31RE90	0.04%	0.03%
PE31	-0.01%	0.04%
PE46RE65	0.10%	0.74%
PE46RE90	0.09%	0.14%
PE46	0.09%	0.15%

Carbon and energy intensity are both projected to decrease across all but one scenario, but there is a greater decline in energy intensity. In the residential sector, the majority of the energy savings from smart grid programs are due to reductions in electricity use and electricity related losses. These projections suggest the complex interactions initiated by the examined rebound effect and price elasticity changes lead towards a shift towards more carbon intensive fuels for electric generation, such as coal. See Appendix E for projected energy intensity, carbon intensity, sectoral energy fuel use, and electric generation fuel graphics.

4.6 Policy Implications

Due to the energy changes induced in other sectors, residential smart grid saves less total energy across all sectors than it does within the residential sector alone. This suggests that sectoral policy impacts cannot be examined in only the sector of focus. The economy wide impacts of policies need to be examined and considered in designing sectoral policies. If not, the realized energy savings might be less than expected and unexpected impacts, such as changes to electric generation fuel mix and fuel prices, with economy wide effects might occur. Based on these projections, residential smart grid might realize more overall total energy savings if accompanied by a suite of cross-sectoral energy policies.

Supportive policies for the commercial and industrial sectors, where the greatest energy increases are projected, might be especially helpful. Smart grid programs can also be implemented in the commercial and industrial sectors, allowing users to be more cognizant of their energy use and prices. Such a suite of smart grid policies may help realize greater energy savings from smart grid programs across sectors than when such programs are implemented individually. Future research should explore the impact of smart grid programs at varying effectiveness in the residential, commercial, and industrial sectors. Similarly, policy support of increased energy efficiency within the commercial and industrial sectors may also help limit the increased energy demand in these sectors with residential smart grid.

Though energy savings are projected in the long term for the electric power sector with these scenarios, electric power sector policies can help counteract projected increases in more carbon intensive fuels like coal. Increasing policy support for less carbon intensive fuels, such as renewable energy, while also implementing residential smart grid programs will likely increase the realized environmental benefits by supporting further CO_2 emissions reductions.

4.7 Conclusions

This chapter examines twelve different scenarios to project economy wide impacts of a national residential smart grid with consumer engagement. These twelve scenarios are divided between high and low rebound effect assumptions for residential heating and cooling end-uses. These scenarios are projected to save a cumulative 3,060 to 8,460 trillion Btu of total energy in the residential sector from 2016 to 2040. Across all sectors, these scenarios are projected to realize a cumulative 2,220 to 7,395 trillion Btu of total energy savings from 2016 to 2040. The energy savings realized by a residential smart grid in the residential and electric power sectors are reduced by increased energy consumption in the commercial, industrial, and, more minutely, transportation sectors. The increases in these three sectors are a form of takeback resulting from the lower electricity prices that occur economy-wide with large-scale energy savings in the residential sector.

Assuming 2013 energy expenditure, the projected savings across all sectors equates to \$0.69 to \$5.5 billion in avoided energy expenditure from these scenarios. If the percentage of energy savings in the residential sector can be maintained across all sectors, then additional avoided energy expenditures may be possible. Projected energy savings in the residential sector ranged from 1.25% to 2.64% across all scenarios. Assuming 2013 energy expenditure, this equates to a range of \$17.3 to \$36.4 billion of avoided energy expenditures.

The energy savings from these projects contribute modestly to the reductions in overall CO_2 emissions, carbon intensity, and energy intensity. These scenarios contribute from -0.01% to 0.74% additional reduction in CO_2 emissions in 2030 when compared to 2005 levels. They assist modestly in realizing the Clean Power Plan emissions goals.

Through examining scenarios with reduced rebound effect and price elasticity of electricity in the residential sector, this study examines the potential impacts from consumer engagement programs from residential smart grid. These scenarios suggest residential smart grid programs have the capacity to significantly reduce national energy consumption and energy expenditures while also helping realize emission reduction goals. However, residential smart grid policies may be more impactful if accompanied by a suite of cross-sectoral policies. Research into the types of cross-sectoral policies that support fuller realization of residential sector savings from residential smart grid across all sectors may be useful. Likewise, further research may be conducted into the scenarios modeling electricity reductions similar to the higher range of experimental studies and the possible economy wide changes. However, from these scenarios, it appears that residential smart grid programs causing the rebound effect and price elasticity changes assumed here, can effectively help realize national energy and environmental goals.

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CHAPTER 5. CONCLUSIONS

5.1 Introduction

Smart grid may not only revolutionize our electrical grid, but also may change how consumers understand and interact with energy and the environment. Smart grid, if implemented widely, will provide a high-tech information interface to every residential household. The majority of U.S. adults obtain their environmental information from only news sound bites. The overall low environmental literacy of the U.S. population may be attributed to the fragmented and incomplete environmental exposure provided by the media (McKeown, 2007). Real-time energy information from smart grid on a large-scale has the potential, if executed thoughtfully, to transform how we interact with not only energy, but also nature and the environment. To effectively realize this opportunity, a greater understanding of effective measures impacting residential energy use is required. The various analyses in this dissertation aim to help better understand residential energy behavior, especially energy savings from efficiency and smart grid measures. For us to understand residential energy behavior and maximize the advantages of smart grid, improved energy study designs and data reporting, increased interdisciplinary energy research, and engagement of the broader public is required.

5.2 Meta-Analysis Energy Efficiency Programs and Opportunities for Improvement

The meta-analysis of residential rebound effect is severely affected by the lack of rigor in residential energy research. Many studies of residential energy efficiency implementation lack large study sizes, random selection of participants, control groups, and controls for confounding factors (Frondel & Schmidt, 2005; Greening, Greene, & Difiglio, 2000; Sorrell, Dimitropoulos, & Sommerville, 2009). The lack of rigorous study designs, the presence of measurement issues, and the exclusion of confounding variables lead many researchers to discount the quasi-experimental literature and to favor econometric findings (Greening et al., 2000). This lack of rigor plagues the quasi-experimental research in the rebound effect literature. It contributes to the lack of trusted evidence that can resolve the longstanding disagreement on the rebound effect. Though more rigorous studies will improve confidence in experimental energy research results, researchers also need to improve consistency in reporting results.

Consistency in reporting energy research findings and more reported details are needed to broaden the usability of research findings. In residential energy efficiency research, there is great inconsistency in what results are reported. Many studies fail to mention theoretical or expected energy savings from measures and only provide energy use after implementing efficiency measures. If expected energy savings are reported, more energy efficiency research can contribute to understanding the residential rebound effect. The inconsistency in reporting and the tendency to apply similar terms to different concepts only further clouds quasi-experimental research contributions.

Limited data reporting severely impacted the meta-analysis of residential rebound effect, which relies on the quasi-experimental literature. Only twenty studies were located that provided expected theoretical energy savings and actual realized energy savings. Without standard deviations or standard errors for much of the data, the meta-analysis relies largely on weighing rebound effect estimates by study size. The meta-analysis finds a moderate average rebound effect of 42% from a random effects model of study level rebound effect estimates. The meta-analysis is limited in its ability to determine what variables impact the rebound effect. Normally, a random effects model should be used given the diversity in study samples and designs, but random effects meta-regression models did not find significant factors. This is likely due to the small sample of located studies. Fixed effects models, though flawed for this application, were used to provide some insight. Studies focused on comfort factor found lower rebound effects than other studies. Since comfort factor largely measures the increase from behavior change, the meta-analysis finds that over 34 percentage points of the rebound effect may be attributed to issues with measurement, implementation, and other inflating factors, holding all else constant. The meta-analysis also finds that different efficiency applications realize different rebound effects. Aspects of study design and lead authorship may also impact the rebound effect estimate. Hopefully improvements in the study design and data reporting from energy efficiency studies will allow a more detailed and larger meta-analysis of residential rebound effect in the future to confirm these findings.

5.3 Impact of AMI Installations

More research on effective energy information and how to relay it may increase energy savings from current smart grid programs. Chapter 3 finds evidence that current U.S. residential smart grid programs, even at this developmental stage, realize energy savings. Holding all else constant, each percentage increase in AMI penetration for residential utility customers decreases the expected average residential electricity by about 0.009%. Even at 100% AMI penetration in residential customers, this would realize a decrease of 0.9% in average residential electricity use. This impact is on the low end of findings from a meta-review of studies providing real-time information feedback where electricity reductions ranged from 0.5% to 18% (Ehrhardt-Martinez, Donnelly, & Laitner, 2010). This suggests several possibilities regarding current residential smart grid. First, though AMI has been incorporated into utilities, information feedback programs may have not been fully implemented. Second, if information feedback programs have been implemented, their design or methods of access may not be optimal for consumer utilization. This analysis did not examine how information was relayed to customers, but if customers have to proactively search for the information (like log into websites), the information may not be conveniently accessible and actionable. Insights from future research on effective information feedback methods will help smart grid programs provide more impactful information.

5.4 Projections of Economy Wide Impacts

Residential energy issues can be complex and have economy wide impacts. In projecting the impacts of a national residential smart grid program in NEMS, Chapter 4 finds residential smart grid to effectively reduce projected energy use in the residential and electric power sectors. At the same time, a residential smart grid induces changes in energy prices, fuel mix, and demand in other sectors. The increase in energy demand from other sectors, especially the commercial and industrial sectors, offsets some of the energy savings realized in the residential and electric power sectors. This suggests that when examining energy policy impacts, the analysis should extend beyond the targeted sector to examine broader, economy wide impacts. Even if an energy policy is successful in its targeted sector, it may induce changes in the economy that impact the overall energy savings. Only a holistic understanding allows the full impact of sectoral policies to be understood.

5.5 Multidisciplinary Efforts and Coordination Needed

Currently, there are unmet opportunities for multidisciplinary research in residential energy behavior. Though there has been substantial human behavior and energy research, more research insights need to be translated to field trials and practice (Allcott & Mullainathan, 2010). In the case of residential energy, there is a need for stronger interdisciplinary research that extends beyond the realm of social scientists, economists, and psychologists. Engineers should be better included in future research. Energy behavior occurs when consumers interact with energy technologies. Just studying behavior alone, separate from technology, presents a false divide. The full system must be examined to understand complex human energy behavior and to design technologies that incorporate social science, psychological, and economic insights.

Given increasingly dire climate change predictions, understanding human energy behavior is an important and necessary step to designing effective technologies and policies to curb energy use. The problem of reducing energy use is not merely an academic one. We all have skin in the game to slow climate change and to better understand why humans use energy as we do. The need for further energy behavior research, improvements in experimental energy research designs, and more consistent reporting are echoed in the literature (Frondel & Schmidt, 2005; Greening et al., 2000; Sanders & Phillipson, 2006; Sorrell, 2009; Sorrell et al., 2009). Researchers have also vocalized the need for more multidisciplinary efforts spanning social science, economics, natural sciences, engineering, and planning to successfully address global goals regarding reductions in fossil fuel use (Stern, Janda, Brown, Steg, Vine, & Lutzenhiser, 2016). Still, many of these issues remain. Perhaps others beyond energy research also should understand the urgency and importance of these issues.

Improved coordination amongst energy researchers and mobilization of consumers may help rapidly increase the knowledge and data available to address residential energy issues. In response to the alarming Zika public health crisis, a multi-disciplinary team of researchers organized to rapidly create a full DNA map of the Aedes aegypti mosquito (Harmon, 2016). Climate change presents a series of challenges to humanity that may dwarf the Zika public health crisis. A similar coordination of research efforts in the energy field could accelerate actionable results to inform real world energy practices. Smart grid success not only depends on technological, regulatory, and legislative innovations, but also heavily hinges on consumer engagement and acceptance (Colak, Fulli, Sagiroglu, Yesilbudak, & Covrig, 2015; Gangale et al., 2013; Sintov & Schultz, 2015; Xenias et al., 2015). Consumer engagement is vital to the success of smart grid information feedback programs. If consumers do not use the information provided, smart grid programs will be unsuccessful in impacting residential energy use. Engagement of the broader public in energy issues may help consumer engagement and acceptance of smart grid technologies.

5.6 Outreach Opportunities to Engage Consumers

Outreach to K-12 students may present opportunities to educate consumers about smart grid technologies and energy while providing opportunities to gather data. Past researchers have utilized K-12 outreach programs in Michigan to combat purple loosestrife. Purple loosestrife is an invasive aquatic plant that, once established, forms thick stands that reduce biodiversity and habitat quality (Landis & Klepinger, n.d.). By raising beetles that consume only purple loosestrife and releasing them in wetlands, classrooms helped to successfully control the invasive population in Michigan while also learning about aquatic systems (Landis & Klepinger, n.d.; Smith, 2012). It is possible to design community outreach programs where teachers are supplied educational materials, trained to teach students about residential energy issues, and engage students in small behavioral studies or investigations. If these school projects are conglomerated on a national or global scale, given the diverse populations reached by effective outreach programs, it is possible to gather behavioral data with larger geographical spread and greater speed than currently possible. Coordination by energy researchers would help ensure consistency in outreach education and design of suggested studies. Designing programs to teach and empower the youth to understand and help solve our current problems, ones that may imperil their futures, may be an effective way to engage consumers in energy issues and increase acceptance of smart grid technologies.

5.7 Summary

Our energy policies promote not only the current energy efficiency environment. They also help craft the energy culture we pass down to our children. "[B]ehavior develops in relation to technologies possessed, and it soon turn[s] into habits and technology-specific acquaintance" (Bladh, 2011, p. 237). This dissertation examines residential energy behavior through three lenses: a meta-analysis of residential rebound effect, an analysis of current residential smart grid, and projections of national residential smart grid programs. Energy efficiency and smart grid both help reduce residential energy use, but residential energy behavior is complex and much still needs to be understood. Decisions at home impact not only the residential sector, but also the whole economy. More and better reported research is required to fully grasp residential energy behavior. The importance of understanding consumer energy decisions cannot be overstated. Understanding how consumers use energy is essential in developing effective energy policies and fully utilizing smart grid technologies. Effective energy policies will not only change our current world, but also impact the energy culture and world future generations inherit.

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APPENDIX A. Rebound Effect Meta-Analysis of Existing Literature

Appendix A.1 Rebound Effect Meta-Analysis Sampling Frame & Search Criteria

The following literature areas were sampled for studies pertaining to residential rebound effect:

- Published peer reviewed literature
- Published non-peer reviewed literature
- Conference proceedings
- White papers
- Utility studies on rebound effect
- Utility studies on energy efficiency studies
- Unpublished literature

Academic databases were used to gather pertinent rebound effect studies from the published academic literature. The following academic databases were used:

- Academic Search Complete
- EconLit
- Google Scholar
- JSTOR
- Web of Knowledge

Non-academic literature was not located through the use of the academic databases. Thus, search engines were used to gather studies from the utility sector and to locate other studies, such as conference presentations and other unpublished works.

- Google
- Yahoo

- Duck Duck Go

A.1.1 Inclusion Criteria

The following inclusion criteria were used to obtain the sample of studies for this meta-analysis. Studies were included if they pertain to:

- Residential rebound effect for all utility usages (electricity, natural gas, and water).
- Residential energy efficiency where enough information is included to calculate the rebound effect
- Calculation of residential rebound effect from empirical results

A.1.2 Exclusion Criteria

Studies were excluded from the sample of rebound effect studies if they pertain only to residential rebound effect in the transportation sector.

A.1.3 Search Terms and Times

The following databases and search engines were used to obtain the preliminary list of pertinent studies. Each is followed by the date on which the search occurred.

1. Web of Knowledge (searched on 6/11/2013)
   - Residential electricity rebound effect NOT modeling
   - Takeback effect
   - rebound effect residential NOT transportation
   - Jevon's paradox
   - Effects of energy efficient technology
   - energy efficiency effect* residential
   - Residential rebound effect NOT transportation
   - Jevons paradox

- Khazoom Brookes
- Utility energy efficiency studies (Searched on 6/12/2013)

2. Academic Search Complete (Searched on 6/12/2013)

    - Residential rebound effect NOT transport*
    - Residential rebound effect NOT transport* AND energy

3. JSTOR (Searched on 6/12/2013)

    - Jevons effect residential energy efficiency
    - rebound effect residential energy efficiency

4. Google (Searched on 6/13/2013)

    - rebound effect residential sector

Appendix A.2 Residential Rebound Effect Meta-Analysis Coding Protocol

The following coding protocol was used to code the pertinent studies for the meta-analysis of residential rebound effect.

A.2.1 Coding for Source Descriptors

1. Publication Year
2. Publication Type
    a. 1 = peer reviewed
    b. 2 = non peer reviewed
    c. 3 = conference
    d. 4 = utility paper
    e. 5 = working paper
    f. 6 = government paper
    g. 7 = other unpublished
3. Discipline of lead researcher
    a. Determined from description of contact information
4. Academic (based on lead researcher)
    a. 1 = academia
    b. 2 = non profit
    c. 3 = utility
5. Impact Factor of Journal
    a. 0 =NA
    b. Actual impact factor written down.
6. Conducted Year (Start year of research)
7. Study Duration

a. Duration of study with unit noted

8. Data Type

    a. 1 = Primary

    b. 2 = Secondary / source

A.2.2 Coding for Sample Characteristics

1. Size of study – size of study in households

2. Country – actual country

    a. Rural (Note: Using U.S. Census Bureau definition of urban areas as having population of 50,000 or more people (2015))

    b. 0 not noted

    c. 1 if rural

    d. 2 if urban

    e. Make notes of location if not initially located

3. House type – type of dwelling / % if available

    a. 0 = not noted

    b. 1 = single family

        i. 2 = duplex

    c. 3 = apartment

4. Income/ % if available

    a. 0 = not noted

    b. 1 = low income

    c. 2 = middle income

    d. 3 = high income

5. Age – if mentioned presence of individual of this age

a. 0 = none noted
b. 1 = elderly / % if available
c. 2 = children / % if available

6. Rent
    a. 0 = own / % if available
    b. 1 = rent / % if available
7. control group
    a. 0 = no control group
    b. 1 = control group
8. Random sample
    a. 0 = not random sampling
    b. 1 = random sampling
9. Monitor
    a. 1 = Metered continuously
    b. 2 = Metered or checked at intervals
    c. 3 = self-report
10. Notes on monitor situation
11. Price
    a. 1 = pricing scheme implemented
    b. 0 = no pricing scheme implemented
12. Price Notes
    a. Notes on pricing scheme
13. Survey

a. 0 = no survey or assessment of house made

b. 1 = house surveyed for energy efficiency

14. Survey Notes

a. Text on survey description

15. Missing Data Notes

16. RE preferred (percentage)

a. Value preferred/mentioned as rebound effect by author

b. Rebound effect defined as decimal less than engineering estimate. So if 15% rebound effect, then realized energy savings only 85% of engineering estimate and rebound effect reported as 0.15.

17. RE low

a. Lower bound of RE

18. RE high

a. Higher bound of RE

19. RE Page

a. Note page where RE estimates come from

20. Standard Error

A.2.3 Coding for Variables

1. Month
    a. Notes month for which estimates take place.
2. End Use
    a. End use examined for rebound effect
        i. 1 = heating
        ii. 2 = cooling
        iii. 3=water heating
        iv. 4= lighting
        v. 5 = appliances
        vi. 6= other
3. Type of efficiency implemented / % if available
    a. 1 = Heating
    b. 2 = Cooling
    c. 3= Water Heating (new water heater)
    d. 4 = Insulation (all types of insulation measures, regardless of location)
    e. 5 = Weatherization (caulking, air proofing)
    f. 6 = Appliances (other than water heaters)
    g. 7 = Thermostat
    h. 8 = Windows
    i. 9 = Lighting

4. Fuel use / % if available
    a. 1= electricity
    b. 2 = natural gas
    c. 3 = other
    d. 4 = both electricity and natural gas
5. Weather
    a. 0 = no consideration
    b. 1 = HDD considered
    c. 2 = other considered
6. Capital
    a. 0 = no consideration/mention
    b. 1 = consideration of capital

Appendix A.3 Final Studies in Rebound Effect Meta-Analysis

The following studies were collected and coded for the rebound effect meta-analysis.

The list includes 21 studies since Scheer (1996) is cited within Haas and Biermayr (2000).

A.3.1 List of Collected Studies

Bell, M., & Lowe, R. (2000). Energy efficient modernisation of housing: a UK case study. *Energy and Buildings*, *32*(3), 267-280.

Bennear, L. S., Lee, J. M., & Taylor, L. O. (2013). Municipal rebate programs for environmental retrofits: An evaluation of additionality and cost-effectiveness. *Journal of Policy Analysis and Management*, *32*(2), 350-372.

Bladh, M. (2011). Energy efficient lighting meets real home life. *Energy Efficiency*, *4*(2), 235-245.

Davis, L. W. (2008). Durable goods and residential demand for energy and water: evidence from a field trial. *The RAND Journal of Economics*, *39*(2), 530-546.

Davis, L. W., Fuchs, A., & Gertler, P. (2014). Cash for coolers: evaluating a large-scale appliance replacement program in Mexico. *American Economic Journal: Economic Policy*, *6*(4), 207-238.

Elmroth, A., Forslund, J., & Rolén, C. (1984). Measured energy savings in Swedish homes. *Energy and Buildings*, *6*(1), 39-54.

Gram-Hanssen, K., Christensen, T. H., & Petersen, P. E. (2012). Air-to-air heat pumps in real-life use: Are potential savings achieved or are they transformed into increased comfort?. *Energy and Buildings*, *53*, 64-73.

Haas, R., & Biermayr, P. (2000). The rebound effect for space heating empirical evidence from Austria. *Energy Policy*, *28*(6), 403-410.

Henderson, G., Staniaszek, D., Anderson, B., & Phillipson, M. (2003). Energy savings from insulation improvements in electrically heated dwellings in the UK. In *Proceedings, European Council for an Energy-Efficient Economy*.

Hewett, M. J., Dunsworth, T. S., Miller, T. A., & Koehler, M. J. (1986). Measured versus predicted savings from single retofits: a sample study. *Energy and Buildings*, *9*(1), 65-73.

Hirst, E., White, D., Goeltz, R., & Mckinstry, M. (1985). Actual electricity savings and audit predictions for residential retrofit in the Pacific northwest. *Energy and Buildings*, *8*(2), 83-91.

Hirst, E. (1986). Actual energy savings after retrofit: electrically heated homes in the Pacific northwest. *Energy*, *11*(3), 299-308.

Hirst, E., Goeltz, R., & Trumble, D. (1989). Effects of the Hood River Conservation Project on electricity use. *Energy and Buildings*, *13*(1), 19-30.

Hong, S. H., Oreszczyn, T., Ridley, I., & Warm Front Study Group. (2006). The impact of energy efficient refurbishment on the space heating fuel consumption in English dwellings. *Energy and Buildings*, *38*(10), 1171-1181.

Martin, C., & Watson, M. (2006). Measurement of energy savings and comfort levels in houses receiving insulation upgrades. *Energy Saving Trust*.

Meier, A., Nordman, B., Miller, N. E., & Hadley, D. (1989). The data behind the Hood River analyses. *Energy and Buildings*, *13*(1), 11-18.

Roy, J. (2000). The rebound effect: some empirical evidence from India. *Energy Policy*, *28*(6), 433-438.

Sanders, C., & Phillipson, M. (2006). *Review of differences between measured and theoretical energy savings for insulation measures.* Energy Saving Trust Report.

Scheer, P. (1996). *Energieeinsparung durch thermische Gebäudesanierung*. Institut für Energiewirtschaft. Vienna University of Technology: Vienna.

Scheer, J., Clancy, M., & Hógáin, S. N. (2013). Quantification of energy savings from Ireland's home energy saving scheme: an ex post billing analysis. *Energy Efficiency*, *6*(1), 35-48.

Sebold, F. D., & Fox, E. W. (1985). Realized savings from residential conservation activity. *The Energy Journal*, *6*(2), 73-88.

APPENDIX B. Derivation of Rebound Effect Standard Deviation Relationship

The equation for sample standard deviation is:

$$s = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}}$$

Given the equation for rebound effect is:

$$RE = \frac{C - A}{C} = 1 - \frac{A}{C}$$

where C is the calculated or theoretical savings and A is the actual savings.

Then, the sample standard deviation for the rebound effect is:

$$s_{RE} = \sqrt{\frac{\left(\left(1 - \frac{A_1}{C}\right) - \left(1 - \frac{A_{Ave}}{C}\right)\right)^2 + \cdots + \left(\left(1 - \frac{A_N}{C}\right) - \left(1 - \frac{A_{Ave}}{C}\right)\right)^2}{N-1}}$$

$$= \sqrt{\frac{\left(-\frac{A_1}{C} + \frac{A_{Ave}}{C}\right)^2 + \cdots + \left(-\frac{A_N}{C} + \frac{A_{Ave}}{C}\right)^2}{N-1}} = \sqrt{\frac{\left(\frac{A_{Ave} - A_1}{C}\right)^2 + \cdots + \left(\frac{A_{Ave} - A_N}{C}\right)^2}{N-1}}$$

$$= \sqrt{\frac{\frac{(A_{Ave} - A_1)^2 + \cdots + (A_{Ave} - A_N)^2}{C^2}}{N-1}} = \sqrt{\frac{(A_{Ave} - A_1)^2 + \cdots + (A_{Ave} - A_N)^2}{(N-1)C^2}}$$

$$= \frac{s_{AS}}{C}$$

where s_{RE} is the sample deviation for the rebound effect, A_1 is the actual or realized savings for the i[th] household, A_{Ave} is the average savings for the sample, C is the calculated savings, N is the sample size, and s_{AS} is the sample deviation for the actual or realized savings.

APPENDIX C. Meta-Analysis Results

The forest plot for the fixed effects model from the *metaan* command is presented below.

The overall estimated effect size is 0.88.

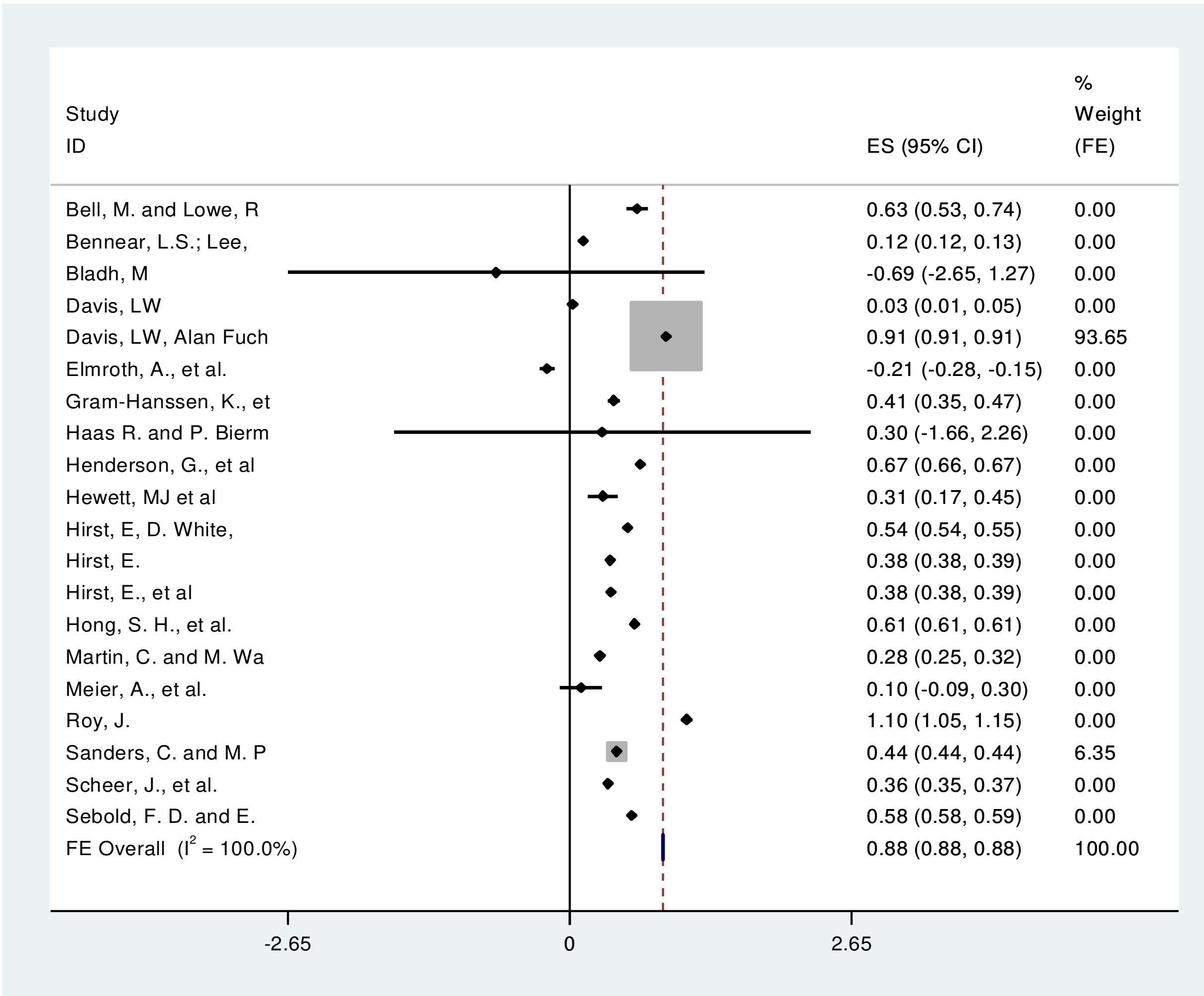

Figure C-1. Fixed Effects Model Forest Plot using Study Level Estimates

APPENDIX D. Results NEMS Scenarios with High Assumed Rebound Effects

This sections provides some of the graphics for the scenarios with high assumed rebound effects for residential heating and cooling end uses.

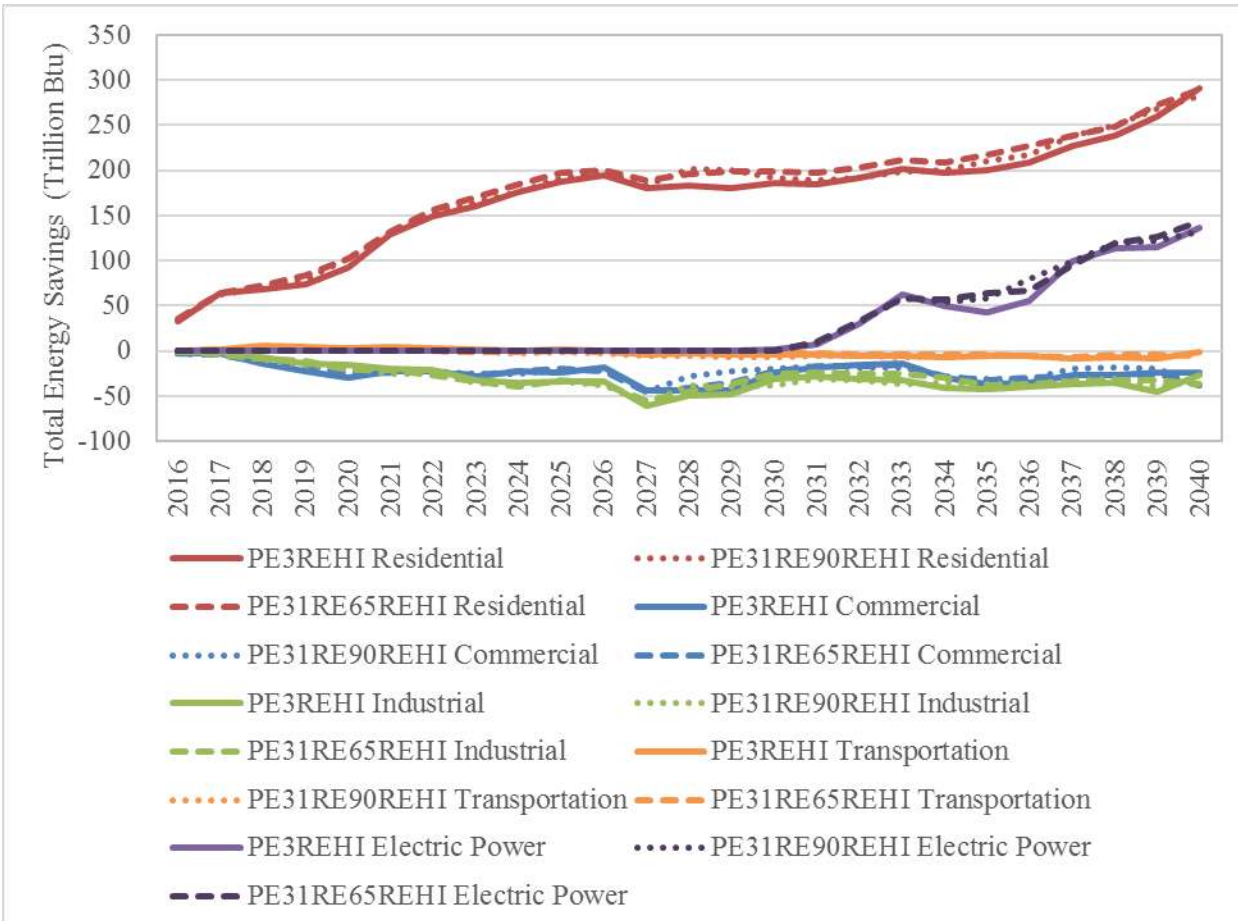

Figure D-1. Total Energy Savings by Sector, High Rebound Effects & Price Elasticity -0.31

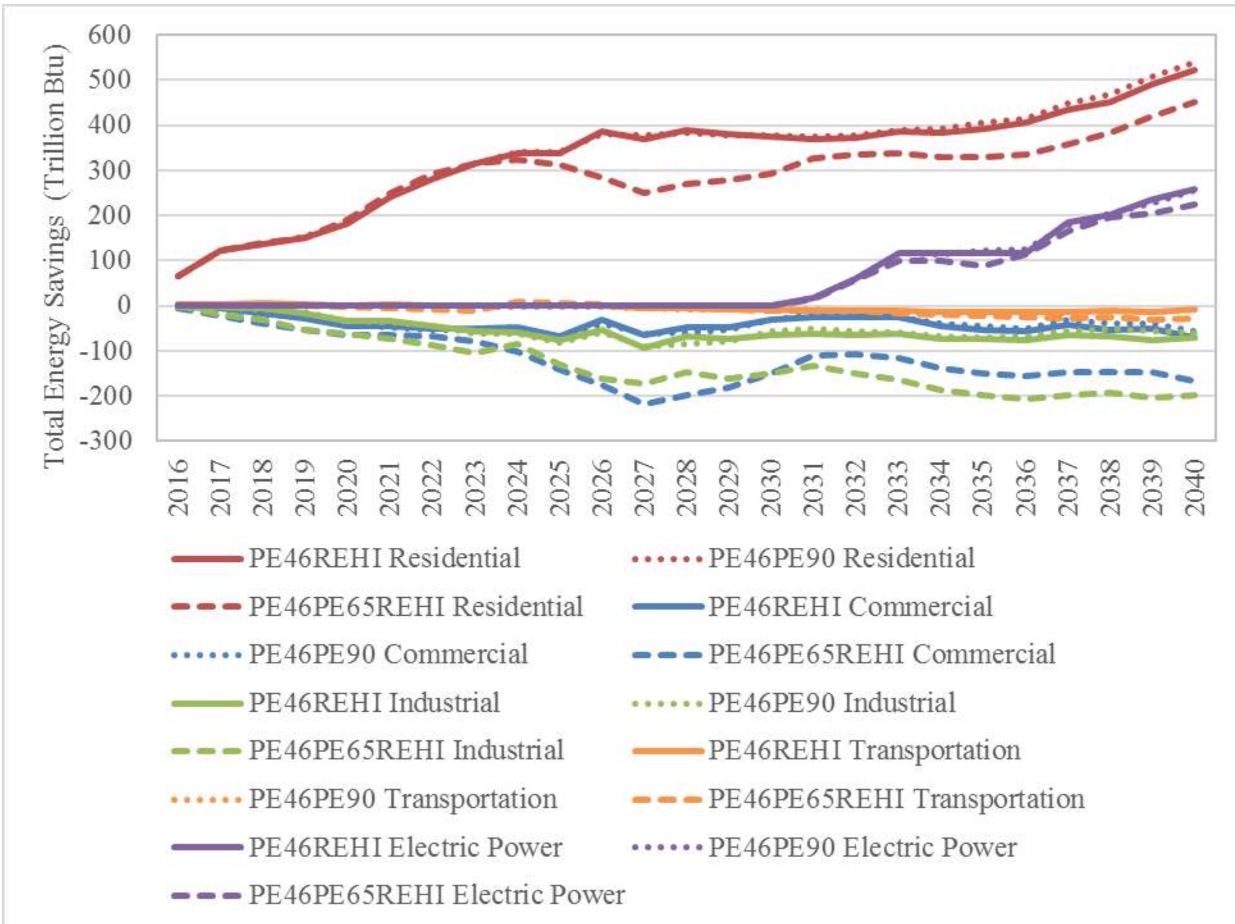

Figure D-2. Total Energy Savings by Sector, High Rebound Effects & Price Elasticity -0.46

Table D-1. Percentage Savings of Total Sector Energy Use in 2040*

Sector	REF15	PE31	PE31RE90	PE31RE65	PE46	PE46PE90	PE46PE65
Residential	1.46%	1.41%	1.37%	1.41%	2.55%	2.64%	2.20%
Commercial	-0.15%	-0.11%	-0.18%	-0.18%	-0.34%	-0.27%	-0.80%
Industrial	-0.07%	-0.07%	-0.09%	-0.10%	-0.19%	-0.16%	-0.53%
Transportation	-0.01%	-0.01%	-0.01%	-0.02%	-0.03%	-0.03%	-0.11%
Elec. Power	0.35%	0.33%	0.32%	0.35%	0.63%	0.62%	0.54%
TOTAL	0.23%	0.20%	0.20%	0.22%	0.05%	0.39%	0.35%

*If the percentages are negative, then total energy use increases and no energy is saved within that sector.

APPENDIX E. Details on Emissions and Other Impacts of NEMS Scenarios

This section provides details on emissions and other impacts from the all examined scenarios.

Appendix E.1 Cumulative Changes in Energy Use by Sector by Fuel Type, 2016-2040

The following charts detail cumulative changes in energy use by energy type and scenario from 2016-2040. Energy savings in the residential sector largely arise from reductions in electricity and electricity related losses. See Table E-1 and E-2 for low and high rebound effect scenarios, respectively.

Table E-1. Cumulative Changes by Energy Type from 2016-2040 for Low Rebound Effect Scenarios, Residential Sector (Trillion Btu)

	PE31	PE31RE90	PE31RE65	PE46	PE46RE90	PE46RE65
Petroleum and Other Liquids	-5.586	-11.46	-26.64	-9.91	-16.10	-31.76
Natural Gas	75.74	38.37	-80.64	88.76	48.06	-29.56
Renewable Energy	0.405	0.472	0.835	0.733	0.665	1.297
Electricity	-1,537	-1,565	-1,675	-2,984	-3,013	-3,069
Delivered Energy	-1,466	-1,537	-1,781	-2,905	-2,981	-3,129
Electricity Related Losses	-2,600	-2,789	-2,931	-5,161	-5,282	-5,347
Total	-4,066	-4,326	-4,712	-8,066	-8,263	-8,476

Table E-2. Cumulative Changes by Energy Type from 2016-2040 for High Rebound Effect Scenarios, Residential Sector (Trillion Btu)

	PE31	PE31RE90	PE31RE65	PE46	PE46RE90	PE46RE65
Petroleum and Other Liquids	-4.681	-7.42	-13.33	-8.98	-12.09	-7.73
Natural Gas	24.83	-4.03	-41.19	20.29	-10.46	195.74
Renewable Energy	-0.265	-0.667	-0.341	-0.328	-0.273	-180.772
Electricity	-1,556	-1,587	-1,619	-3,025	-3,056	-3,211
Delivered Energy	-1,537	-1,599	-1,674	-3,014	-3,078	-3,204
Electricity Related Losses	-2,727	-2,792	-2,829	-5,285	-5,338	-3,949
Total	-4,263	-4,391	-4,503	-8,299	-8,417	-7,153

In the commercial sector, cumulative electricity and natural gas use both increase across low rebound effect scenarios from 2016 to 2040 (See Table E-8). However, in the high rebound effect scenarios, natural gas use in the commercial sector is largely projected to decrease over the period (See Table E-9). Projected changes in other fuel use are dwarfed by the changes in natural gas and electricity use. The bulk of the increased energy use in the commercial sector is from electricity and electricity related losses. All main energy types are shown, with the exception of renewable energy for the commercial sector where no changes occurred.

Table E-3. Cumulative Changes by Energy Type from 2016-2040 for Low Rebound Effect Scenarios, Commercial Sector (Trillion Btu)

	PE31	PE31RE90	PE31RE65	PE46	PE46RE90	PE46RE65
Petroleum and Other Liquids	0.353	0.152	0.151	0.180	0.303	0.391
Natural Gas	86.71	88.04	62.00	47.97	57.60	93.30
Coal	0.002	0.053	0.017	0.043	0.044	0.058
Electricity	114.7	127.7	106.3	181.8	194.9	227.8
Delivered Energy	201.7	216.0	168.5	229.9	252.9	321.5
Electricity Related Losses	630.7	518.8	550.6	1,039	997.7	1,109
Total Energy	832.4	734.7	719.1	1,269	1,251	1,430

Table E-4. Cumulative Changes by Energy Type from 2016-2040 for High Rebound Effect Scenarios, Commercial Sector (Trillion Btu)

	PE31	PE31RE90	PE31RE65	PE46	PE46RE90	PE46RE65
Petroleum and Other Liquids	0.347	0.245	0.030	0.351	0.283	336.877
Natural Gas	-24.59	-27.08	-20.87	-80.59	-95.87	267.65
Coal	-0.008	-0.010	-0.004	0.011	0.002	0.304
Electricity	110.2	89.2	94.8	158.3	142.6	-22.8
Delivered Energy	86.0	62.4	74.0	78.1	47.0	582.0
Electricity Related Losses	530.3	482.6	520.7	947	922.3	2,363
Total Energy	616.3	545.0	594.7	1,025	969	2,945

In the industrial sector, petroleum, natural gas, coal, electricity, and renewable energy use are projected to increase when compared to the revised reference case for all scenarios. The bulk of the projected consumption increase is from more natural gas and electricity use for low rebound effect scenarios (See Table E-5). Projected electricity use increases more than other fuels in the industrial sector for high rebound effect scenarios (See Table E-6).

Table E-5. Cumulative Changes by Energy Type from 2016-2040 for Low Rebound Effect Scenarios, Industrial Sector (Trillion Btu)

	PE31	PE31RE90	PE31RE65	PE46	PE46RE90	PE46RE65
Petroleum and Other Liquids	38.90	46.46	49.09	100.5	97.04	107.4
Natural Gas	189.7	212.3	192.0	256.9	193.0	299.5
Coal	38.26	38.94	41.41	82.09	81.13	92.39
Biofuels Heat and Coproducts	2.592	0.283	2.493	3.935	-8.267	2.655
Renewable Energy	22.09	22.74	24.55	51.92	49.87	57.39
Electricity	105.9	116.7	111.3	201.5	199.8	236.0
Delivered Energy	397.5	437.3	420.8	696.8	612.6	795.4
Electricity Related Losses	518.4	434.4	481.3	918.6	864.0	971.0
Total	915.8	871.8	902.1	1,615	1,477	1,766

Table E-6. Cumulative Changes by Energy Type from 2016-2040 for High Rebound Effect Scenarios, Industrial Sector (Trillion Btu)

	PE31	PE31RE90	PE31RE65	PE46	PE46RE90	PE46RE65
Petroleum and Other Liquids	44.52	43.25	37.41	101.4	90.68	691.2
Natural Gas	65.8	67.8	56.7	66.3	52.8	521.8
Coal	50.00	47.82	42.52	85.62	83.21	97.12
Biofuels Heat and Coproducts	3.587	2.735	1.260	0.546	0.352	-10.947
Renewable Energy	29.08	29.72	25.08	52.30	50.58	109.26
Electricity	109.4	111.5	98.1	193.3	180.7	3.2
Delivered Energy	302.4	302.9	261.0	499.4	458.3	1,411.7
Electricity Related Losses	455.8	454.7	449.1	866.2	848.3	1,849.1
Total	758.2	757.6	710.1	1,366	1,307	3,261

Appendix E.2 Electricity Generation

The scenarios also impact the projected fuel mix for electricity generation. The scenarios induce small but variable changes to the electric generation fuel mix. See Figure E-1 and E-2 for an example of select fuel mix changes for the PE31RE65 scenario for low and high rebound effect assumptions, respectively. In this scenario, fuel switching within the electric power sector occurs. Coal use increases and natural gas use mostly decreases throughout the projection period. Nuclear energy increases for the majority of the projection period, while renewable energy largely decreases during the projection period. This suggests that coal and nuclear energy generated electricity supplant a portion of natural gas and renewable energy generated electricity in this scenario. If smart grid policies are accompanied by additional policies that reduce incentives to use coal for electricity generation, more environmental benefits may accrue.

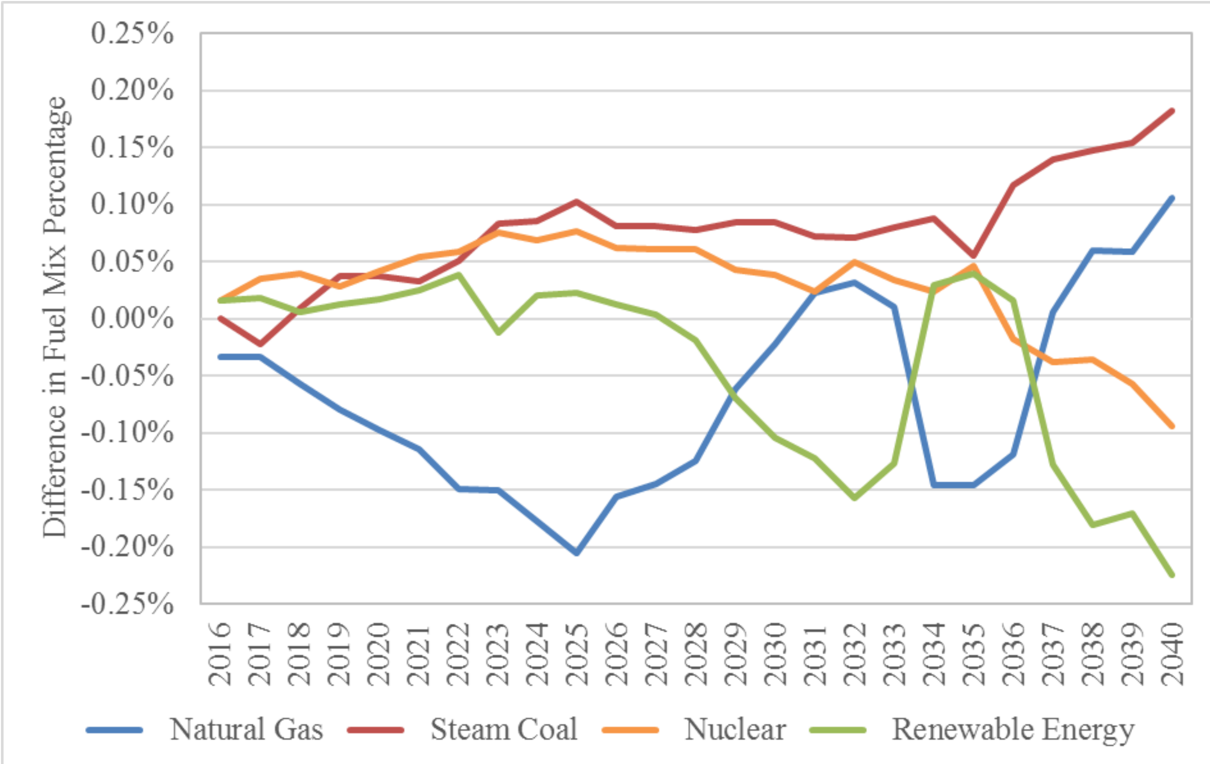

Figure E-1. Select Electric Generation Fuel Mix Changes for PE31RE65 Scenario

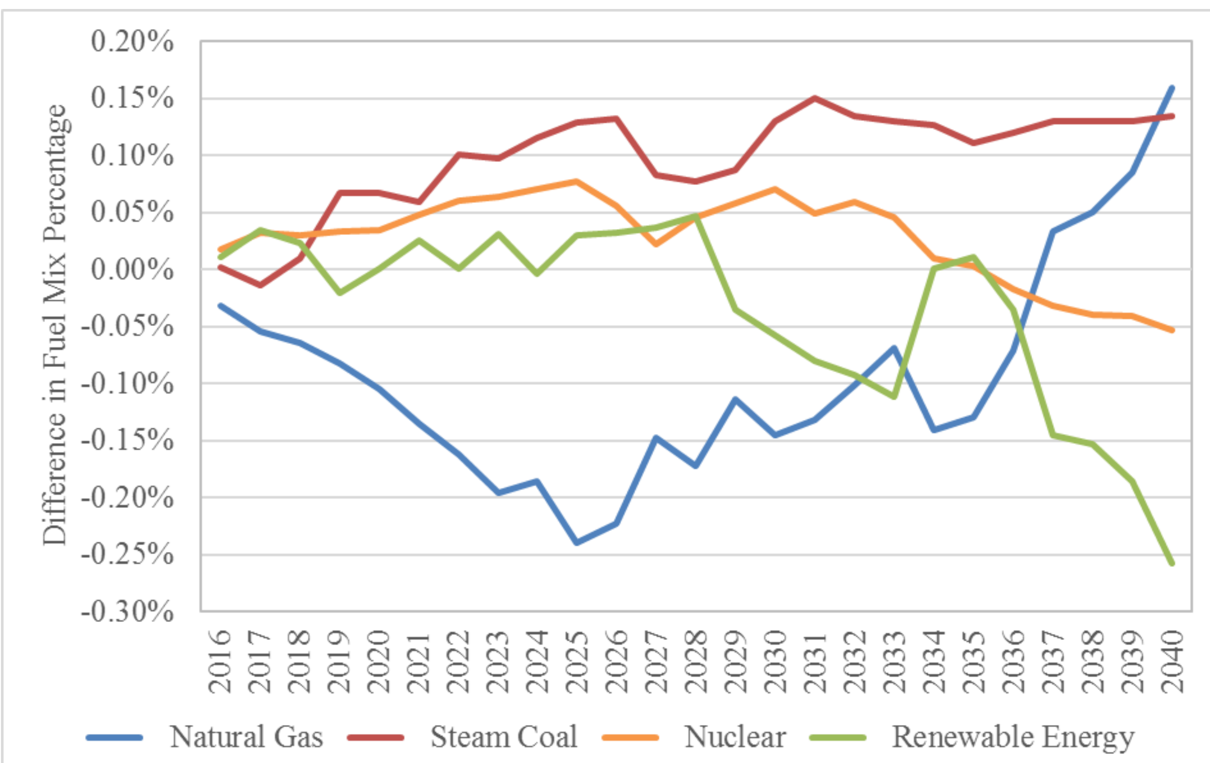

Figure E-2. Select Electric Generation Fuel Mix Changes for PE31RE65REHI Scenario

As seen in Figure E-1, the changes in fuel mix fluctuate for different years within the projection. In 2020, all scenarios project increased steam coal, nuclear, and renewable energy use and decreased natural gas use. In 2040, however, all scenarios project decreased nuclear and renewable energy generation with the exception of PE46RE65 for high rebound effect assumption scenarios. Coal use increases, as does the use of distillate and residual fuel oils. Non-biogenic municipal waste and electricity imports also increase. The impact on natural gas is more mixed, with some scenarios projected to increase its use and others projected to decrease its use for electric generation in 2040. See Figure E-3 and E-4 for bar charts of the projected fuel mix changes by scenario in 2020 for low and high rebound effect assumption scenarios, respectively. See Figure E-5 and E-6 for bar charts of the projected fuel mix changes by scenario in 2040 for low and high rebound effect assumption scenarios, respectively.

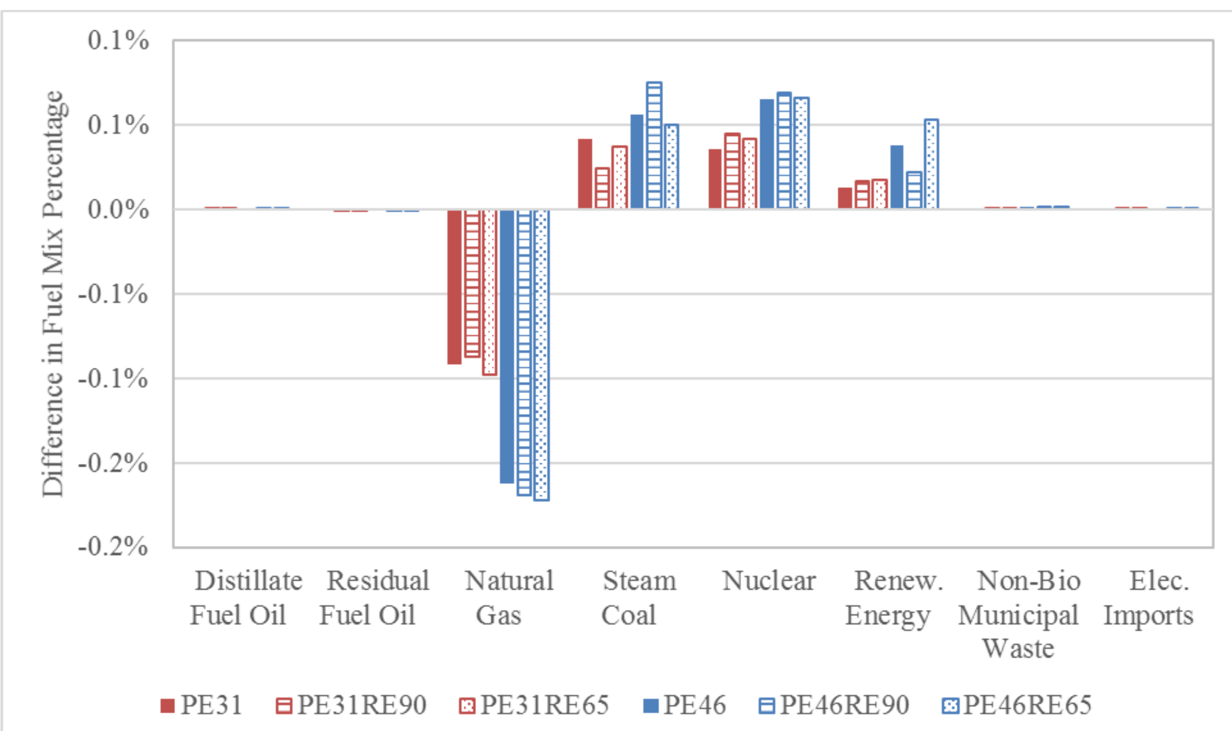

Figure E-3. Electric Generation Fuel Mix Changes in 2020, Low Rebound Effect Scenarios

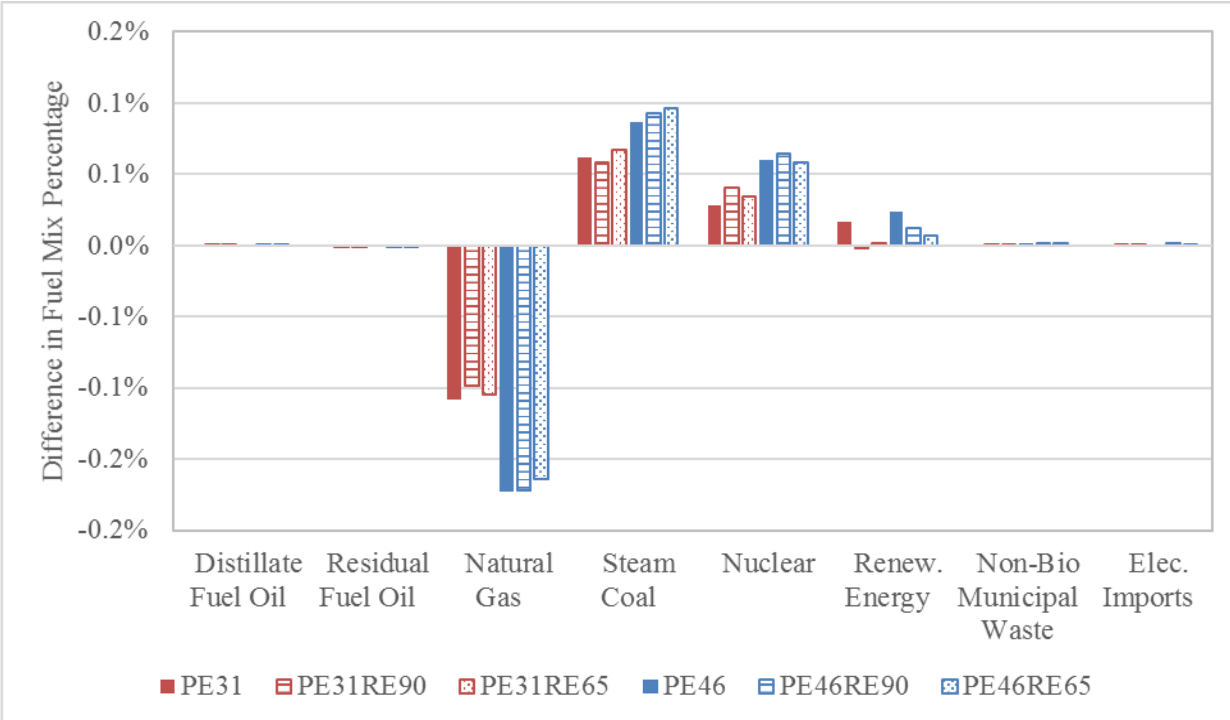

Figure E-4. Electric Generation Fuel Mix Changes in 2020, High Rebound Effect Scenarios

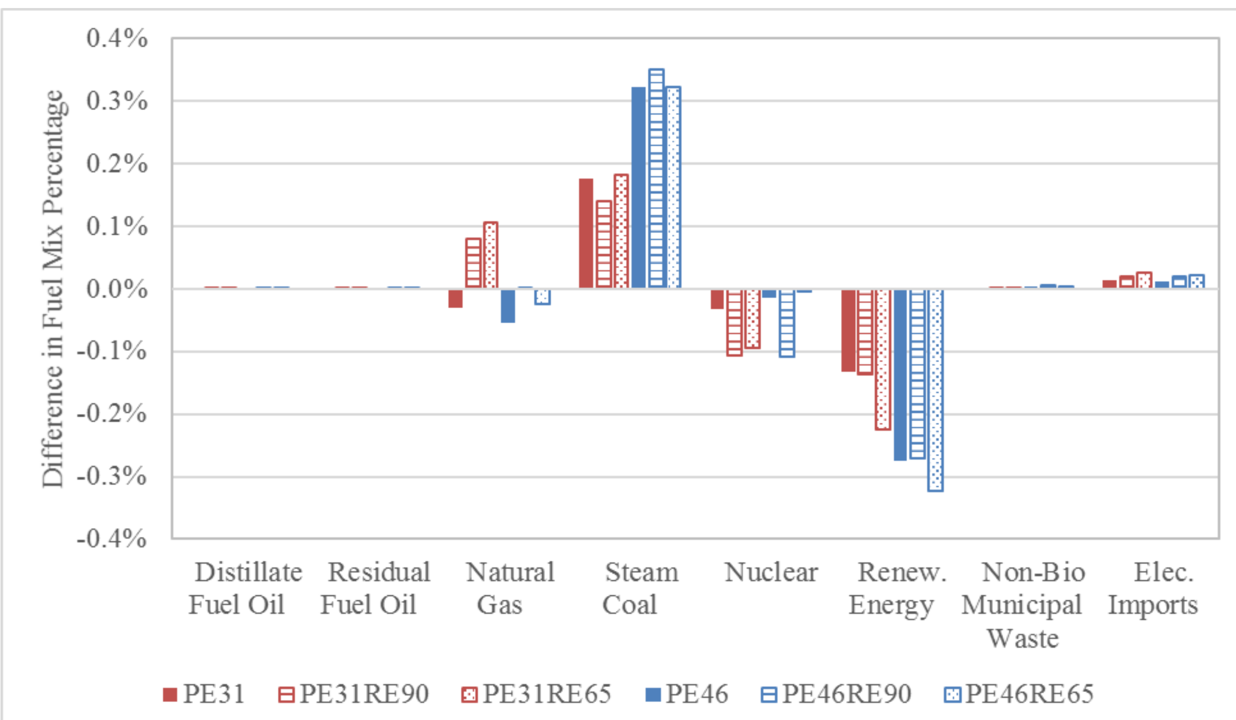

Figure E-5. Electric Generation Fuel Mix Changes in 2040, Low Rebound Effect Scenarios

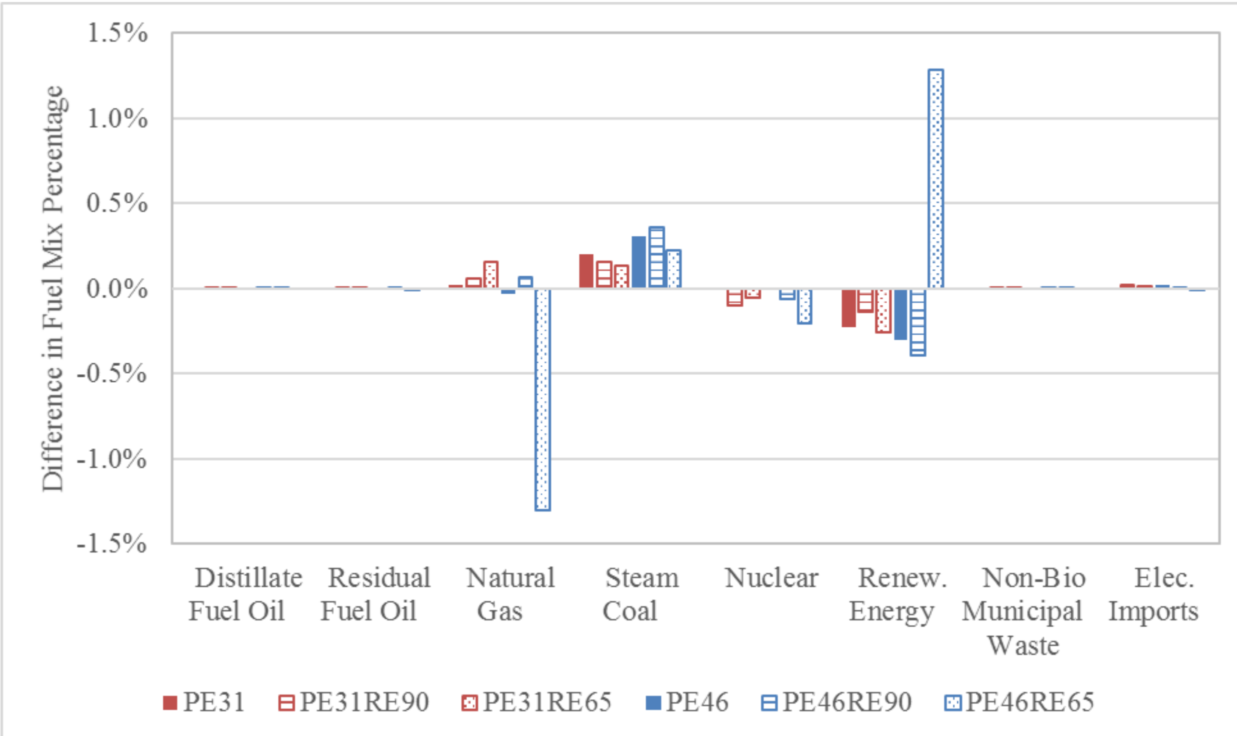

Figure E-6. Electric Generation Fuel Mix Changes in 2040, High Rebound Effect Scenarios

Appendix E.3 Energy and Carbon Intensity

The following charts show energy and carbon intensity for all scenarios over time as a percent difference from the pertinent revised reference case scenario. In general, the decline in energy intensity is greater than the decline in carbon intensity, suggesting that there is a projected switch to more carbon intensive fuels with these scenarios.

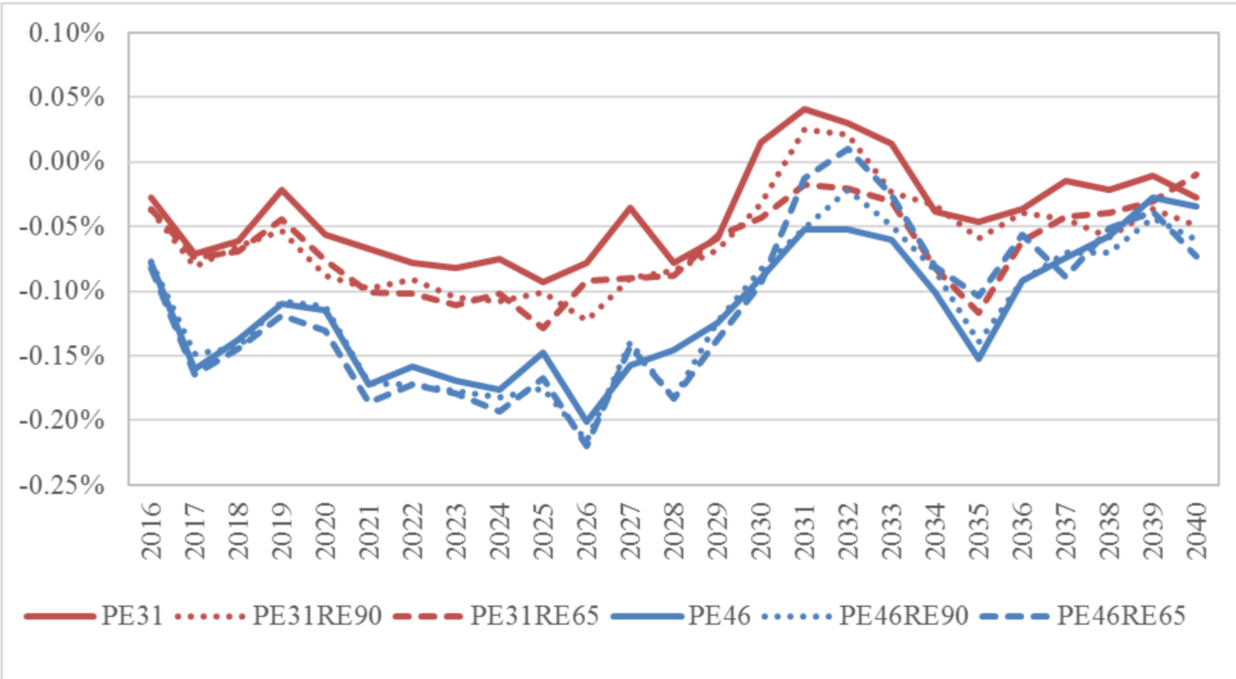

Figure E-7. Percentage Difference in Carbon Intensity from Revised Reference, Low Rebound Effect Scenarios

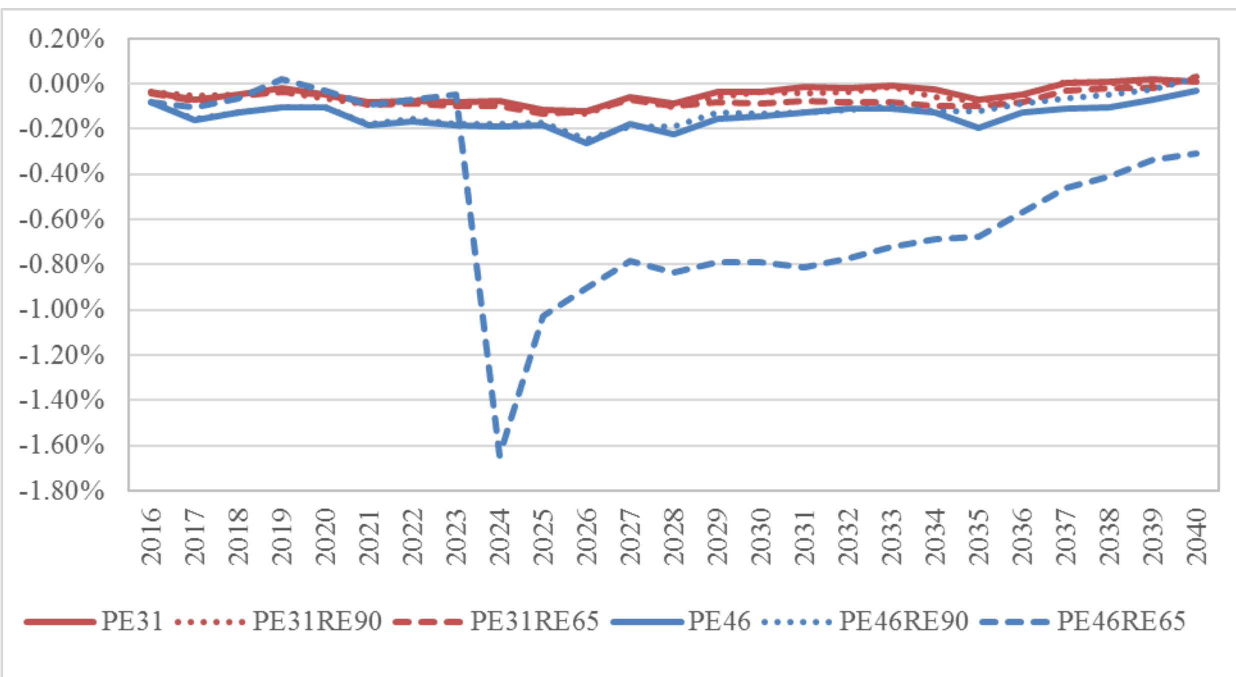

Figure E-8. Percentage Difference in Carbon Intensity from Revised Reference, High Rebound Effect Scenarios

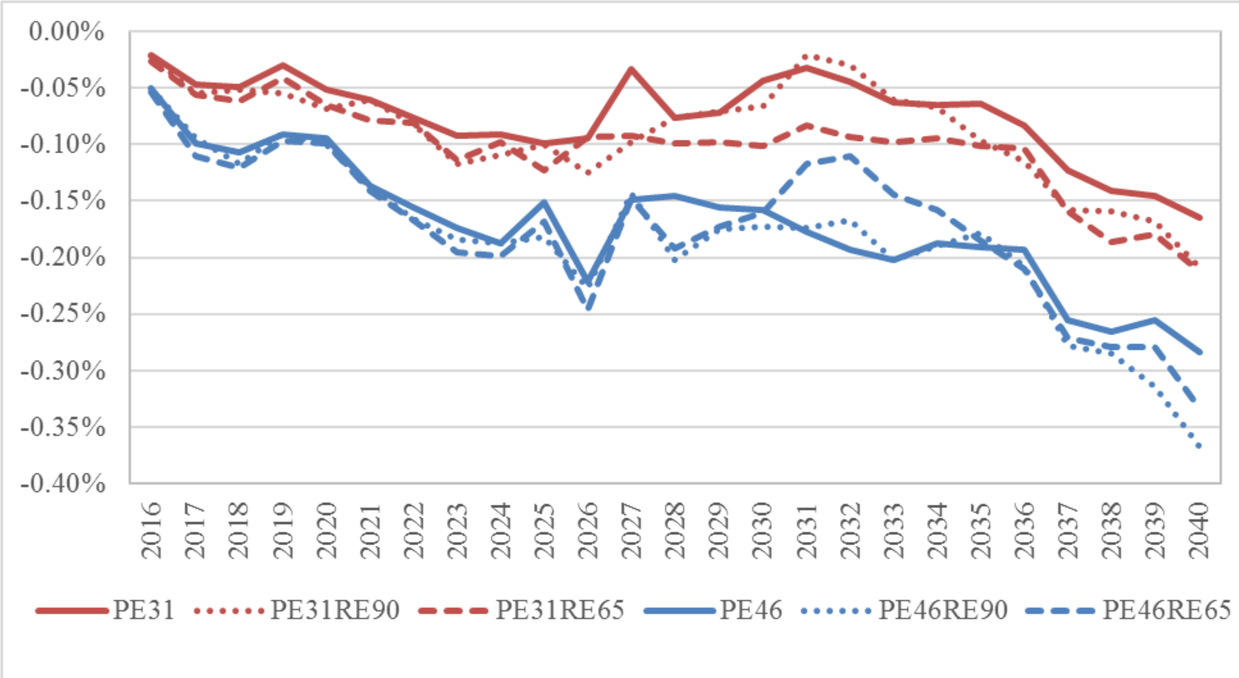

Figure E-9. Percentage Difference in Energy Intensity from Revised Reference, Low Rebound Effect Scenarios

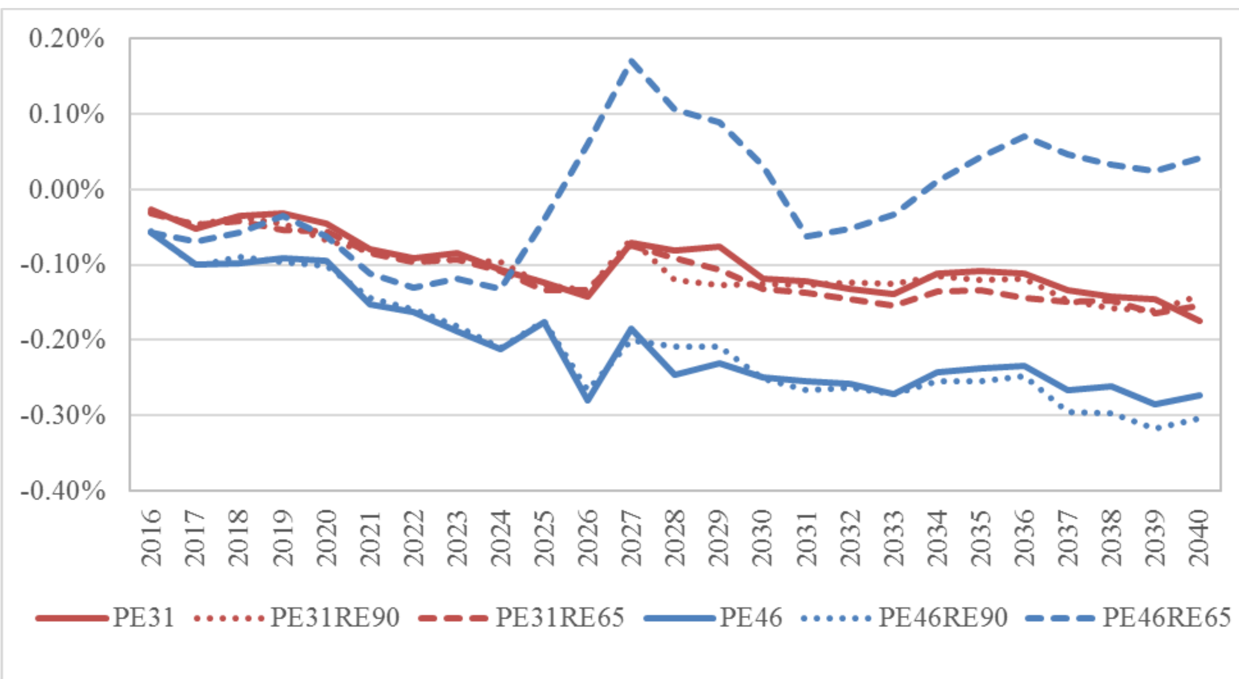

Figure E-10. Percentage Difference in Energy Intensity from Revised Reference, High Rebound Effect Scenarios