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Electricity Generation, Electricity Consumption, and Energy Efficiency in the United States: A Dual Climatic-Behavioral Approach

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Environmental Dynamics

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Abstract

Much of the United States (US) has seen an increase in warm days, decrease in cool days, and increase in extreme weather events. These trends are projected to continue across much of the US and in turn increase the demand for electricity and subsequent greenhouse gas emissions. Ambitious energy efficiency (EE) programs are used across the US by energy utility organizations to reduce electricity demand and emissions. This study examined the impact of climatic variability on electricity consumption, as well as how pro-conservation interventions such as EE programs and experiential learning can be utilized to mitigate residential electricity consumption and emissions. Chapter 2 of this study examined the impact of EE programs on residential electricity consumption taking into account climatic indicators across the contiguous US. A state-by-state analysis suggested that climatic indicators were more explanatory of residential consumption than energy utility organization EE efforts at the state-level. Chapter 3 examined residential electricity consumption for heating and cooling applications explained by energy utility organization EE efforts and climatic indicators in the Southeast US. Indirect spending on EE programs was significantly related to heating and cooling applications and heating degree days, a climatic indicator for number of days over a certain temperature, were significantly related to cooling equipment applications. A survey of 2,450 residential electricity consumers was analyzed. Residents who were aware of EE programs and participated in EE programs were significantly more likely than those who were not to support energy utility organization use of clean energy and government subsidies for EE programs. Chapter 4 provided case study in a Southeast US state where a pro-conservation behavioral intervention was deployed in an elementary school. This chapter utilized a longitudinal design and mixed methodology to assess the effect of curriculum-based experiential learning on environmental

literacy and electricity-saving behaviors. Students showed improvement in environmental literacy after interventions were deployed. Normalizing electricity consumption for weather, a decrease in energy consumption of more than 15% in student homes and more than 30% at the focal school was observed. The final chapter provides a discussion of the findings, implications, future research questions, and conclusions.

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Articles

- Chapter 2: Craig, C. A., Feng, S. (2016). Exploring utility organization electricity generation, residential electricity consumption, and energy efficiency: A climatic approach. Applied Energy (in review).
- Chapter 3: Craig, C. A. (2016). Energy consumption, energy efficiency, and consumer perceptions: A case study for the Southeast United States. Applied Energy 165, 660 669 (published).
- Chapter 4: Craig, C. A., Allen, M. W. (2015). The impact of curriculum-based learning on environmental literacy, energy consumption, and policy. Utilities Policy 35, 41 49 (published).

Chapter 1: Introduction

1.1 Introduction

Climatic variability and extreme weather events are a consequence of anthropogenic interaction with the natural environment (IPCC, 2014). Carbon dioxide (CO₂) levels continue to rise and are the most salient contributor to climate change among greenhouse gases (GHG; IPCC, 2014). There have been efforts in the United States (US) and internationally to curb GHG emissions (e.g., Gilleo et al., 2014; United Nations (UN), 2015), however, emissions continue to rise (Energy Information Agency (EIA), 2015a; National Oceanic and Atmospheric Association (NOAA), 2016a). In 2015, leaders of over 40 organizations with \$1.2 trillion US dollars in yearly revenue joined together to proclaim that climate change is real and action is needed to protect both societal and organizational interests (Open letter, 2015). This sentiment was resounded at the UN Conference on Climate Change in Paris in 2015 where leaders from around the world committed to limit climate change related to GHG emissions (UN, 2015).

Numerous negative consequences have occurred and / or are projected to occur related to climatic variability and extreme weather events. For instance, between 1980 and 2015, extreme weather resulted in 188 billion dollar disasters that affected the US (NOAA, 2016b). The increased intensity of climatic variability and extreme weather events are projected to increase financial losses by up to 3.9 times above current losses in the US (Ingram et al., 2013; IPCC, 2014; Preston, 2013). Increased climatic variability, including extreme heat and warmer days, is also projected to increase the demand for electricity across the US (Jovanovic et al., 2015; McFarland et al., 2015; Mideksa & Kallbekken, 2010). Population growth and increased population density, particularly in coastal regions, pose major risks to infrastructure, resource availability, human health, and social-service support (Allen, 2016; Shen et al., 2009; World

Resources Institute, 2014). The Southeast US is environmentally and financially vulnerable to increased temperature, drought, and extreme events (Craig, 2016; NOAA, 2016b; Preston, 2013). The reliance on fossil fuels for electricity generation in combination with proportionally high electricity reliance from heating and cooling equipment (EIA, 2015a; EIA, 2009) increase the vulnerability in the region to climate change.

The overarching goal of the current study is to better understand how climatic variability and pro-conservation interventions are related to electricity consumption. This study sought to gain a clearer understanding of how pro-conservation interventions can be utilized to reduce GHG emissions related to electricity consumption and generation. The use of the theory of planned behavior (TPB; Ajzen, 1991), messaging framing, and experiential learning to increase awareness in EE, participation in EE, and support for GHG reducing policy are examined. Chapters 2 – 4 explore study objectives along a macro-micro continuum with residents across the US, in a single Southeastern US state, and in a single community. The remainder of the introduction will discuss the focal stakeholders (i.e., energy utility organizations and residential electricity users), theory application, knowledge gaps, and the rationale for compiling Chapters 2 – 4.

1.2 Literature review

Below, energy utility organizations – the stakeholder group that supplies the most electricity – will be discussed followed by residential electricity consumers – the stakeholder group that consumes the most electricity. The application of the TPB will then be discussed.

1.2.1 Energy utility organizations

Energy utility organizations continue to be a leading contributor to GHG emissions as electricity consumption rises across multiple sectors. Accordingly, the focal organizational

stakeholder is the energy utility organization. Since the 1850's, energy and cement producing organizations have been the primary producers of CO₂, accounting for over 60% of the production worldwide (Heede, 2014). The vast majority of the emissions are in the energy sector, making the use of fossil fuels for generation the most salient contributor to CO₂ emissions (Heede, 2014). Energy utility organizations generate and transmit electricity for consumption by end-users, including both residential and organizational consumers.

On the aggregate, electricity generation and electricity consumption have been closely related across the United States (Craig & Feng, 2016b). Historically, the US has consumed approximately four times as much electricity as the highest overall electricity consumer in the world, China (EIA, 2015b), on a per capita basis. Both countries' CO₂ emissions continue to rise (EIA, 2015b; Heede, 2014; Zhao et al., 2014). CO₂ emissions from all electricity fuel sources has declined since 2007 in the US (EIA, 2015a). However, a shift to natural gas for electricity generation by energy utility organizations has increased the intensity of other GHG emissions including methane (EIA, 2015a; IPCC, 2014). Despite the overall decrease in CO₂ emissions directly attributed to electricity generation in the US, GHG emissions remain at historically high levels, regions around the US remain reliant on fossil fuels for electricity generation, and electricity consumption and generation continue to increase (EIA, 2015a; EIA, 2015c; IPCC, 2014; NOAA, 2016a).

There is public support for utility use of clean energy (Craig & Allen, 2014; Craig, 2016; Jacobe, 2013) and an international consensus to combat CO₂ emissions (UN, 2015). In 2013 over 70% of Americans supported a greater emphasis on the use of wind and solar power (Jacobe, 2013). However, energy utility organizations across the US and the states in which they reside are opposed to federal regulations that reduce emissions (Biesecker, 2015). For instance, many

fossil fuel reliant states contested emission reducing regulations that would require a shift away from the fuel sources in the US Supreme Court case Michigan et al. v. Environmental Protection Agency et al. (2015). The majority of electricity is generated by investor-owned utility (IOU) organizations in the US (EIA, 2015a). Approximately 94% of electricity sales are from IOUs at 71%, followed by cooperative providers and municipal providers accounting for 12% and 11% of sales, respectively (EIA, 2014). According to data obtained from the EIA (2014), the remaining sales are from federal, state, and political subdivision providers. IOUs are accountable to shareholders, and outside regulation or other intervening factors will pursue profit-seeking behavior (Sioshansi, 2013) such as continued use of fossil fuel reliant electricity generation infrastructure. Accordingly, profit-seeking behavior by IOUs has the potential to result in societal cost (Weimer & Vining, 2011) such as the adverse effects of climate change associated with continued electricity generation from GHG emitting fossil fuels.

Energy utility organizations offer energy efficiency (EE) programs across the US in an effort to reduce electricity consumption and generation. EE was encouraged as early as the 1970's in response to oil shortages, and federal regulation focused on energy conservation was passed in 1979 (Sioshansi, 2013). EE and conservation moved from a focus on the supply towards management of energy demand in the 1990's, and today an integrated approach that includes managing and / or responding to energy demand is common (Sioshansi, 2013). Many energy utility organizations operate EE programs that provide incentives for residents and organizations to reduce electricity consumption to help reduce electricity demand (Allcott & Greenstone, 2013). In its most basic form, "EE is a measure of how resourcefully energy is used" (Nilsson et al., 2013, p. 91). According to Gilleo et al. (2014), EE can help electricity consumers "meet their needs by using *less* energy," (p. v) resulting in economic, environmental, and social

benefits. Examples of EE efforts include (but are not limited to) lighting retrofits, installation of smart meters, installation of motion sensors, increased insulation, duct sealing, and rebates in retailers for efficient appliances. To quantify the current size of the EE market around the world, spending was estimated between 310 US dollars and 360 US dollars in 2011 and is expected to increase exponentially (International Energy Agency, 2014).

The manner in which utility EE programs are regulated, climatic variability, and inconsistent and / or fluctuating electricity usage make it difficult to determine actual electricity savings achieved by EE programs. National EE and GHG energy reduction efforts, including efficiency ratings on appliances and GHG reduction targets, have federal oversight from agencies including the Department of Energy and the Environmental Protection Agency (EPA) (American Council for an Energy-Efficient Economy (ACEEE), 2016a). At the state-level, regulators have oversight for electricity usage rates, EE program offerings, and the costeffectiveness of EE program offerings (Alcott & Greenstone, 2013; Schurr & Hauser, 2013). Cost-effectiveness occurs when the cost of an EE incentive is lower than the cost of saved energy (Alcott & Greenstone, 2013). Currently, 25 states have in place Energy Efficiency Resource Standards (EERS), which are binding long-term efficiency targets (ACEEE, 2016b). EERS states have short-term between year targets for energy savings that contribute to long-term goals, and in 2014 EERS states achieved approximately 4 times more incremental energy savings than non-EERS states (ACEEE, 2016b). Energy utility organization EE programs have regulatory oversight at the state-level, where the majority of programs from IOUs are funded by EE riders and paid by customers based on consumption (Craig & Allen, 2014).

The effectiveness of state-level EE programs and the ability to accurately quantify electricity savings is complicated by several characteristics of EE offerings including a rebound

effect and the method by which EE savings are claimed and reported. First, a "rebound effect" is common after EE upgrades where projected electricity savings are not realized when rich feedback about upgrades and / or energy usage are not provided (Delmas et al., 2013; Gillingham et al., 2013; Greening et al., 2000). It is also difficult to quantify climatic interaction with actual electricity savings from EE program offerings. The electricity savings and EE incentives are not traditionally based on observed savings, rather on a deemed savings model that assigns kilowatthour (kWh) values to the specific EE offering taking into account past weather conditions (Craig, 2016; Craig & Allen, 2014). EERS primarily rely on deemed savings to determine if targets are met. For instance, kWh savings may be based on estimated usage time and wattage of a light bulb rather than an observed kWh reduction. Deemed savings can also influence the costeffectiveness of EE program offerings. Cost-effective EE programs that offer the largest gap between incentive levels and energy savings are most often pursued by energy utility organizations; energy savings for which incentives are provided are traditionally determined using a deemed savings rate. The combination of the rebound effect and use of a deemed savings model complicates the understanding of the true impact of EE programs on electricity consumption.

1.2.2 Residential electricity consumers

Residential electricity consumers are the largest consumer group in the US, and electricity consumption continues to increase (EIA, 2015c). Accordingly, the focal electricity consumer in the current study is the residential consumer. Residential electricity consumption in the US is the largest consuming sector followed by the commercial and industrial sectors (EIA, 2015c). Unlike some organizational electricity consumers, residential consumers are primarily charged for electricity based on volumetric, fixed pricing, making it difficult to curtail residential

electricity demand (Schurr & Hauser, 2013). Information asymmetry occurs when real-time information about electricity consumption is not made available to consumers, when information is misleading, or when information is difficult to understand. This can lead to inefficient market conditions that make it prohibitive for consumers to engage in pro-conservation behaviors.

Residents not responding to price cues is particularly problematic during times of peak electricity generation, or maximum capacity, because of increased production costs for energy utility organizations and the fossil fuel reliant energy mix used to meet the demand (Craig & Feng, 2016a). GHG emissions from increased residential consumption is a concern during peak electricity demand conditions. Craig & Feng (2016a) found that increased electricity consumption in months with more hot days shared was most significantly related to electricity generation from GHG emitting fossil fuels. That is, when demand exceeded the typical – or baseload – electricity generation, the additional demand was primarily met by fossil fuels.

Residential EE programs are often utilized by energy utility organizations to avoid peak electricity demand conditions, also known as demand-side management (DSM). Peak electricity production conditions increase the cost of generation. DSM and demand response programs are designed to reduce electricity demand by introducing technologies to increase efficiency and / or providing feedback to residents about electricity usage either prior to or during peak conditions (Pinto et al., 2015; Spence et al., 2015). The effectiveness of residential EE programs including DSM have shown mixed results, due in part to the lack of response to extreme weather and peak demand conditions. For instance, in a meta-analysis of residential incentive programs from 1975 until 2012, Delmas et al. (2013) found that incentives for efficiency upgrades that did not include feedback about the upgrade and / or energy usage information resulted in increased consumption. That is, when incentive programs aimed at reducing electricity demand did not include feedback,

a rebound effect occurred where more electricity was consumed. Likewise, in a recent study by Asensio and Delmas (2015) economic feedback was found to not be the optimal strategy to achieve persistent residential electricity savings. Gillingham et al. (2013) stated that the initial electricity savings of efficiency efforts in the home are approximately 10%, but these savings can be offset by factors such as increased electricity use or purchase of new products that use additional electricity. Greening et al. (2000) observed the rebound effect in residences after efficiency efforts as well. Responsive DSM EE programs that engage residents with information about electricity use have consistently demonstrated electricity reduction (e.g., Asensio & Delmas, 2015).

Residents are unique compared to organizational users in terms of motivation for conserving electricity, further warranting the inclusion as the focal electricity consumer sector. For instance, the economically derived business case is often used to justify sustainability initiatives in organizations (Allen, 2016; Blackburn, 2007). However, many non-economic factors motivate individuals to engage in pro-environmental behaviors, such as reducing residential electricity consumption. Previous research suggests that socio-demographics such as age, gender, political affiliation, health, income, and home size can influence pro-conservation intentions and behaviors (Abrahamse & Steg, 2011; Aktamis, 2011; Asensio & Delmas, 2015; Brouhle & Khanna, 2012; Coffey & Joseph, 2013). The manner in which a message is framed, the topic of a message, and the medium of a message have also demonstrated significant relationships with individual environmental behaviors, intentions, and perceptions (Asensio & Delmas, 2015; Craig & Allen, 2014; Craig & Allen, 2013; Pelletier & Sharp, 2008).

To combat increased electricity consumption following EE efforts, or the rebound effect, state regulatory bodies are increasingly approving the use of behavioral focused approaches by

energy utility organizations to enhance electricity savings (Gilleo et al., 2014). Asensio and Delmas (2015) were successfully able to longitudinally quantify electricity reduction in residences as a result of behaviorally-focused messaging campaigns. Lynch and Martin (2013) reported a 5.8% reduction in residential electricity consumption using a longitudinal behavioral design, and Fisher (2008) reported between a 5% and 12% reduction in consumption from behavioral change alone. Traditional utility EE program measures used for residential DSM include efficient technologies such as light bulbs, as well as home improvements such as added insulation or heating and cooling upgrades (e.g., Asensio & Delmas, 2015; Craig & Allen, 2014; Spence et al., 2015). However, electricity savings in the home are more salient when residents are aware of and / or have engaged in efficiency behaviors prior to efficient upgrades (Liu et al., 2015). A combination of efficient technologies and behavioral interventions can maximize electricity savings in the home (Craig & Allen, 2015).

While economic rationale and incentive programs can be effective, occupants of homes and organizations need to be knowledgeable about how to save electricity and empowered to act. Currently, engagement with EE offerings remains low (e.g., Craig & Allen, 2014; Langevin et al., 2013). One approach to increase knowledge and engagement favored by many energy experts around the world is to provide environmental and energy education in elementary schools (Sovacool, 2009). In addition to enhancing student knowledge, environmental programs in K-12 schools have also successfully reduced consumption in school facilities (e.g., Cross et al., 2010). This was the approach taken in Chapter 4. However, educational programs in the US are primarily voluntary, rarely enacted because of time / curriculum constraints, and are subject to political resistance among state legislatures (e.g., Craig & Allen, 2015; Miller, 2012).

Allcott and Mullainathan (2010) stated that non-price behavioral interventions such as policy implementation and awareness campaigns are needed to combat shortfalls of economic-focused intervention. Claudy and O'Driscoll (2008) contended a cost-benefit, economic approach in and of itself may not be the right approach when considering grants and / or subsidies related to efficiency. Rather, the authors supported an integrated approach that takes into account individual behaviors, context, and economics. The greatest electricity-savings results are likely when a holistic approach is taken that includes efficiency technologies / upgrades common with utility EE programs as well as behavioral interventions targeting individuals (Craig & Allen, 2015). Now that the salient stakeholder groups have been discussed, an overview of the theoretical application for the study will be provided.

1.2.3 Theory of planned behavior

The TPB contends that attitudes, perceptions, and norms precede behavioral intentions, which in turn precede actual behavior (Ajzen, 1991). The TPB is a micro-level theory that incorporates perceived behavioral control related to a focal topic. Throughout the chapters of this study, the focal topic of interest is residential electricity consumption / conservation. Awareness is a necessary component of behavior change as predecessor to the elements of the TPB (Egmond & Bruel, 2007), however, the direct effect of awareness on behavior change is not widely supported (Allen, 2016). The TPB has been widely used in a variety of disciplines, and has received wide support when operationalized as a predictive model for both behaviors and behavioral intentions. For instance, in a meta-analysis of 185 studies Armitage and Connor (2001) found that the TPB explained 27% of variability in actual behaviors and 39% in behavioral intentions. The difference between actual behavior and behavioral intentions is widely noted in the environmental literature, where there is a "gap between access, awareness,

knowledge, attitudes, planned behavior, and actual pro-environmental behavior" (Craig & Allen, 2014, p. 226).

The TPB has successfully explained variability in a multitude of pro-conservation behaviors such as residential recycling (e.g., Cialdini, 2003; Nigbur et al., 2010). Specific to electricity consumption by residential consumers, quantitative studies have demonstrated that the TPB is predictive of electricity reducing behaviors and intentions (Abrahamse & Steg, 2011; Brosh et al., 2014; Chen, 2016; Lynch & Martin, 2013). Lynch and Martin (2014) found that observed electricity consumption reduced by over 5% in homes that received communication consistent with the TPB not controlling for climatic factors, and Brosh et al. (2014) demonstrated that TPB variables explained 34% of the variation in residential intention to engage in energy-saving behavior. Specific to common electricity-using consumer goods, attitudinal factors were the most influential for intentions to curb use (Lo et al., 2014). However, the use of norms to influence behavioral intentions were mixed. Also, Clement et al. (2014) found that for temperature regulation and other home energy conservation in a residence, attitudes and behavioral control were significantly related but subjective norms were not.

Combined, findings from previous studies highlight the importance of using awareness, engagement, and experience to build positive attitudes and perceived behavioral control among residents. The mixed and insignificant findings related to norms suggest there may be a lack of accountability for reducing electricity in the home that communicative mechanisms could potentially overcome. Unlike recycling, normative pressures from others may not be as high about conserving electricity because it is not as visible to others.

In this study, the TPB is applicable as it captures inputs that influence residential awareness, perceptions, attitudes, and behaviors pertaining to EE programs, electricity reduction,

and energy utility organization reduction of GHG emissions. The TPB captures intrinsic characteristics of individual residents. Chapter 2 found that climatic factors were more salient predictors of residential electricity consumption than EE programs around much of the US. Consistent with previous studies (e.g., Abrahamse & Steg, 2011; Brosh et al., 2014; Chen, 2016; Craig, 2016; Lynch & Martin, 2013), Chapter 2 suggested that the use of behavioral mechanisms by energy utility organizations, including environmental messaging, can improve awareness about EE programs, potentially resulting in more positive individual attitudes / perceptions towards EE programs, and in turn improve participation in EE programs. Messaging can draw from persuasive models such as the TPB to more successfully influence individual attitudes towards electricity conservation, empower individuals to believe they have control over conservation behaviors, and engage in electricity conservation. By providing messaging that builds awareness and encourages positive attitudes / perceptions in coordination with incentives for EE offerings, electricity savings are more likely to be achieved and maintained. Consistent with the TPB, Chapter 3 found that residents who were more aware of EE programs were more likely to participate (i.e., behavior) and that residents who participated were more likely to support GHG reduction by utilities. Chapter 3 also demonstrated that perceptions about the energy utility organization differed based on awareness levels, providing additional quantitative support for the role of awareness as a predecessor to other TPB variables. Chapter 4 did not explicitly discuss the TPB. However, concluding remarks in Chapter 5 discuss the applicability of the TPB to increase knowledge / awareness about electricity conservation in schools and communities. Also, the use of norms to achieve actual electricity reduction in homes will be discussed.

1.3 Knowledge gaps

1.3.1 Chapter 2

It has been widely noted that electricity generation from fossil fuels and electricity consumption are salient causes of GHG gas emissions such as CO₂ (e.g., IPCC, 2014; Langevin et al., 2013). However, the relative impact of electricity generation by fuel source type and electricity consumption by consumer segment on GHG emissions from the electricity industry across the US is not well known. To address this knowledge gap, Chapter 2 quantified this relationship. Accordingly, the first research question in Chapter 2 was:

Research question 1: How much of the variability in total US CO₂ emissions is explained by electricity generation and consumption.

As noted in the literature review, the majority of utility EE programs have used a deemed savings approach that does not account for observed climatic conditions. This approach does not capture actual reduction in electricity consumption. To the best of the author's knowledge, there has not been a comprehensive US-wide analysis of actual EE savings that control for actual observed climate interaction. Actual kW per resident were used to quantify the electricity reduction from EE efforts in lieu of deemed savings. McFarland et al. (2015) noted that future projections of electricity demand take into account climatic factors, however, efficiencies are notably missing from the models. Also, previous research has suggested mixed and negative results from EE offerings (e.g., Delmas et. al., 2013; Gillingham et al., 2013). The TPB is introduced in Chapter 2 to discuss how messaging can be utilized to increase awareness and promote participation in states where EE savings were not significantly related to residential electricity consumption. To address the knowledge gaps of climatic and EE program impact on residential electricity consumption, the research questions were posed:

Research question 2: How strong are the relationships residential electricity consumption share with CDD, HDD and kW reduction from EE at the state-level?

Research question 3: How much of the variability in residential electricity consumption is explained by CDD, HDD, and kW reduction from EE at the state-level?

1.3.2 Chapter 3

Chapter 3 focused on a single state in the Southeast US. This region is particularly environmentally and economically vulnerable to climate change (Ingram et al., 2013; Preston, 2013). The knowledge gap of climatic and EE impact on residential electricity consumption was addressed in Chapter 3 as well. In addition to the actual kW savings used in Chapter 2, this chapter also included direct (i.e., incentive) costs as well as indirect (i.e., marketing, administrative) costs. To the best of the author's knowledge, this was the first study of its kind to examine the interaction of observed climatic indicators with EE savings, incentive costs, and indirect program costs. Information asymmetry from energy utility organizations has made it exceedingly difficult to assess the relative effectiveness of EE programs. This chapter also included a method to allocate kWh consumption to heating and cooling applications to help overcome the gap related to information availability and / or resolution associated with annual utility reporting. As such, the first research question was posed:

Research Question 1: How much variability in kWh consumption used for heating and cooling is explained by climatic factors, EE program actual kW savings, and EE costs.

There is a widely noted gap in the literature between knowledge, attitudes, and perceptions with electricity conserving behaviors that is magnified by historically low levels of engagement in utility EE efforts (Craig & Allen, 2014). Chapter 3 sought to better understand this gap in terms of demographic and TPB variables to inform future GHG reduction efforts in

the region. The impact of message framing on perceptions about energy utility organization motives for offering EE programs, and residential support for utility GHG reducing activities were also explored. Implementers of EE programs and policy makers alike often lack clear direction about how to successfully design interventions to reduce residential electricity consumption and to build support for policy to combat climate change and / or to adhere to regulatory requirements. The combination of quantifying the effectiveness of EE programs at reducing consumption and a comprehensive analysis of residents in the social science portion of the chapter provided direction for these stakeholder groups. Accordingly, the following research questions were posed:

Research Question 2a: Is there a difference between residential consumer participation in EE programs based on residential electricity consumer awareness levels?

Research Question 2b: Is there a difference in perceptions about utility motives for providing efficiency programs, and support for utility use of clean energy based on residential electricity consumer awareness levels, participation in utility programs, and demographic factors?

1.3.3 Chapter 4

Chapter 4 focused on a single community and single elementary school in a Southeast US state. Sovacool (2009) noted that deployment of efficiency through schools is a desirable strategy to increase engagement and learning throughout communities. Behavioral programs that incorporate student learning have shown success at promoting efficiency and electricity reduction in schools (Bulman & Ehrendreich, 2010; Cross et al., 2010) To the best of the author's knowledge this was the first study to quantify efficiency and electricity savings in student homes following a school-level intervention. Schools have been successful deployment

mechanisms to encourage positive behaviors of students and families such as wearing seat belts (National Highway Traffic Safety Administration, 2008). Community support can also help encourage pro-conservation in homes (Staats et al., 2004). Specific to electricity savings, normative influence has shown mixed or non-significant results relative to pro-conservation behavioral intentions or actual behaviors (Clement et al., 2014; Lo et al., 2014). Chapter 5 will discuss how experiential learning and occupant engagement presented in Chapter 4 can promote normative influence from the TPB and result in actual pro-conservation behaviors.

Programs aimed at efficiencies in schools remain voluntary, however, and often do not make it into the classroom or into the community. While materials are available, funding for deployment of specific pro-conservation interventions in schools remains a challenge. Energy utility organizations spend over \$7 billion annually on EE programs (Gilleo et al., 2014), however, the allocation toward schools is relatively low and the focus is on the school facility, not the occupant. Chapter 4 addressed the funding and adoption gaps for school-based programs by providing a model that can be used to cost-effectively deploy curriculum-based interventions in schools, and subsequently into communities. The experiential learning model can be used to overcome the gap between intentions and behaviors for pro-conservation behaviors with other focal groups as well. Accordingly, the following hypotheses were posed:

Hypothesis 1: A combination of classroom and experiential exercises at school and home about energy usage can increase student knowledge about energy.

Hypothesis 2: Students can reduce their household's energy consumption.

Hypothesis 3: Energy consumption at the school will decrease over the course of behavioral change interventions.

1.4 Chapter rationale

The body of this study consists of three chapters from two previously published original research articles and one original research article that has been revised and is in review.

Combined, the three chapters help to achieve a clearer understanding of how climatic variability, EE, and other pro-conservation interventions can influence electricity consumption. The body of the study explores theory and practice to provide guidance as to how to best develop and deploy pro-conservation interventions to increase knowledge and enact behaviors. As discussed in the following, all chapters considered a macro-micro continuum regarding stakeholders, used a systems-level approach, and used quantitative models and methodology to address the goals of the study.

1.4.1 Macro-micro continuum

Energy utility organizations provide regulated EE offerings for residents that are used in homes, making it necessary to examine stakeholder relationships in this study along a macromicro continuum. Throughout the study, energy utility organization actions were examined relative to residents. Costs or disadvantages to residents and society range from macro-level issues (e.g., US-wide emissions by fuel source for the entire US discussed in Chapter 2) to micro-level issues (e.g., unequal access to EE programs offered in lower socio-economic communities discussed in Chapter 3 and Chapter 4). The chapters in this study provided insights into a macro-micro continuum for stakeholder relationships necessary to explore the unique nature of energy utility organizations and related product offerings.

Chapter 2 began by addressing US-wide emissions – a macro-level problem – related to generation by fuel source type and electricity consuming sectors. Furthermore, the impact of climatic factor and EE program savings on residential electricity consumption were examined

across the contiguous 48 states in the US. Chapter 3 utilized a macro-micro perspective. The impact of climatic factors and EE spending were examined for a single Southeastern US state, and individual residents were surveyed to explore differences in engagement with utility EE programs and support for GHG reducing policy. And lastly, Chapter 4 took a more micro-level perspective in a single community in the Southeast US. An experiential learning intervention related to electricity conservation was deployed in a single elementary school. The interaction between climatic variability specific to student household was examined. Also, macro-level implications including energy utility organization allocation of funds to school-focused EE programs and national curriculum were provided.

1.4.2 Systems approach

Bapat (2005) integrated social concepts with environmental theory based on a systems approach (Bennett, 1976; Forrester, 1973) to provide a framework to examine the interactions between shared human and environmental processes. A systems-level approach allows for a problem to be quantified, action to be taken to address the problem, feedback to be analyzed, and further action to be taken over time (Forrester, 2009). Bapat (2005) integrated theory from environmental and social sciences to help explain complex processes involving the environment and humans, noting that quantitative modeling can "help human beings understand these processes in a better manner so that they can be subject to manipulation and control." (p. 38). Consistent with Bapat (2005), Chapters 2 – 4 utilized both environmental and resident-focused data to provide quantitative analysis in order to define climatic / electricity consumption problems, to quantify actions by residents, and to inform development of policy and proconservation interventions. Specific models and methodologies were provided in Chapters 2 – 4.

1.4.3 Methodology

In this study, the climatic indicators of interest are heating degree day (HDD) and cooling degree day (CDD). Degree days are the number of days above or below a threshold temperature (EPA, 2014), set at 65° Fahrenheit in Chapters 2 – 4. As demonstrated by Mourshed (2012), HDD and CDD are more accurate predictors for electricity than temperature, thus the two indicators were used here.

In Chapter 2, correlation analysis and stepwise linear regression were utilized to build a model for each state that explained the variability in monthly electricity generation explained by HDD, CDD, and EE peak electricity savings per resident. After developing an equation to allocate electricity consumption to heating and cooling applications, Chapter 3 utilized stepwise linear regression to build a model to explain variability in residential electricity consumption explained by HDD, CDD, and EE spending per resident by state energy utility organizations. Chapter 3 also utilized ANOVA-analysis with variables consistent with the TPB to understand the key differences among state residents related to support for GHG reducing policies and engagement with utility EE program offerings. In terms of systems-thinking, historical climatic and emissions data are indicators of the climate change problem, and EE data is an indicator of societal action to address the problem. ANOVA analysis provided additional insights into residents at a micro-level, and how participation can influence political action to address climatic problems at the macro-level.

Chapter 4 deployed curriculum-based experiential learning interventions among students in a single elementary school. Like Chapters 2 and 3, Chapter 4 included a longitudinal element, and the impact of degree days on residential electricity were examined. A pre- and post-test was

administered to students before and after interventions to quantify student learning. Electricity consumption controlled for HDD for the focal school facility and for student homes was examined year-over-year to quantify the impact of the intervention in terms of electricity savings. A systems approach was applicable here as well. Curriculum-based experiential learning interventions were deployed with elementary students that quantified electricity consumption (i.e., the problem), provided interventions (i.e., action) to reduce electricity consumption in the school and at student homes, and provided feedback as to the outcomes of student actions when controlling for climatic variability. Elementary aged children are capable of understanding systems-level thinking (Forrester, 2009), and policy to provide energy and environmental lessons in schools is an approach supported by many energy experts around the world (Sovacool, 2009).

1.5 Conclusion

Chapter 1 provided an overview of the most salient stakeholders in this study: Energy utility organizations and residential electricity consumers. The focal theory that is applied throughout the study in practice – the TPB – was presented, as were knowledge gaps and the rationale for chapter inclusion. In the remainder of the study, Chapters 2 – 4 will be presented as stand-alone research studies. A discussion will then be provided to discuss key findings from Chapters 2 – 4, implications of the findings, and where future research is needed. Lastly, a conclusion will be presented.

1.6 References

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1.7 Appendix. Internal Review Board approval.



Office of Research Compliance Institutional Review Board

May 25, 2016

M	M	U	V	٩n	U	U	M

TO: Christopher Craig

Song Feng

FROM: Ro Windwalker

IRB Coordinator

RE: New Protocol Approval

IRB Protocol #: 16-05-762

Protocol Title: Electricity Generation, Electricity Consumption, and Energy

Efficiency in the United States: A Dual Climatic-Behavioral

Approach

Review Type:

☐ EXEMPT ☐ EXPEDITED ☐ FULL IRB

Approved Project Period: Start Date: 05/25/2016 Expiration Date: 05/24/2017

Your protocol has been approved by the IRB. Protocols are approved for a maximum period of one year. If you wish to continue the project past the approved project period (see above), you must submit a request, using the form Continuing Review for IRB Approved Projects, prior to the expiration date. This form is available from the IRB Coordinator or on the Research Compliance website (https://vpred.uark.edu/units/rscp/index.php). As a courtesy, you will be sent a reminder two months in advance of that date. However, failure to receive a reminder does not negate your obligation to make the request in sufficient time for review and approval. Federal regulations prohibit retroactive approval of continuation. Failure to receive approval to continue the project prior to the expiration date will result in Termination of the protocol approval. The IRB Coordinator can give you guidance on submission times.

This protocol has been approved for 2,515 participants. If you wish to make *any* modifications in the approved protocol, including enrolling more than this number, you must seek approval *prior to* implementing those changes. All modifications should be requested in writing (email is acceptable) and must provide sufficient detail to assess the impact of the change.

If you have questions or need any assistance from the IRB, please contact me at 109 MLKG Building, 5-2208, or irb@uark.edu.

Chapter 2: Craig, C. A., Feng, S. (2016). Exploring utility organization electricity generation, residential electricity consumption, and energy efficiency: A climatic approach. Applied Energy (in review).

2.1 Abstract

This study examined the impact of electricity generation by fuel source type and electricity consumption on carbon emissions to assess the role of climatic variability and energy efficiency (EE) in the United States. Despite high levels of greenhouse gas emissions, residential electricity consumption continues to increase in the United States and fossil fuels are the primary fuel source of electricity generation. 97.2% of the variability in carbon emissions in the electricity industry was explained by electricity generation from coal and residential electricity consumption. The relationships between residential electricity consumption, short-term climatic variability, long-term climatic trends, short-term reduction in electricity from EE programs, and long-term trends in EE programs was examined. This is the first study of its nature to examine these relationships across the 48 contiguous United States. Inter-year and long-term trends in cooling degree days, or days above a baseline temperature, were the primary climatic drivers of residential electricity consumption. Cooling degree days increased across the majority of the United States during the study period, and shared a positive relationship with residential electricity consumption when findings were significant. The majority of electricity reduction from EE programs was negatively related to residential electricity consumption where findings were significant. However, the trend across the majority of states was a decrease in electricity reduction from EE while residential electricity consumption increased. States that successfully reduced consumption are discussed, in addition to the potential use of communication theory to design interventions aimed at improving EE program success.

Chapter 2: Exploring utility organization electricity generation, residential electricity consumption, and energy efficiency: A climatic approach

2.2 Introduction

This study examines the impact of electricity generation by fuel source type and electricity consumption on carbon emissions to assess the role of climatic variability and energy efficiency (EE) in 48 contiguous United States (US). The continued reliance on fossil fuels for electricity generation in the face of increased climatic variability has led to electricity consumer demand conditions that are largely met by fossil fuel sources (United States Energy Information Agency (EIA), 2015a). Since the 1850s, energy producing organizations have emitted the majority of carbon dioxide (CO₂) emissions, with only 90 organizations worldwide emitting over 60% of the of CO₂ (Heede, 2014). Since 1986, CO₂ emissions have more than doubled globally (Heede, 2014). There are thousands of utility organizations in the US, where investor-owned utility (IOU) organizations produce and supply the vast majority of electricity, and subsequently produce the vast majority of greenhouse gas (GHG) emissions (EIA 2015a). The majority of electricity generation is from coal, and natural gas is the fastest growing fuel source for electricity since 1990 (Figure 1; EIA, 2015a).

Today more than \$7 billion is spent on EE programs in the US (Gilleo et al., 2014).

Demand-reduction EE programs are used in the residential sector as an alternative to volumetric pricing (Schurr & Hauser, 2013). That is, utility organizations cannot respond to increased electricity demand by raising prices. The electricity savings values and overall program budgets for IOU EE programs, as well as electricity rates, are governed by state-level regulatory organizations (Craig & Allen, 2014; Schurr & Hauser, 2013). There is a need for both short- and long-term regulatory practices to meet goals in energy markets (Wang & Tian, 2015). However,

low perceived value for EE incentives, non-responsive pricing, and underdeveloped program offerings deter residential participation (Asensio & Delmas, 2015; Labanca et al., 2015; Schurr & Hauser, 2013). Furthermore, a rebound effect (i.e., more electricity is consumed after an EE measure is implemented) is common when residents are not knowledgeable about EE, have negative attitudes towards EE and / or the IOU, or do not receive adequate feedback about EE upgrades (Asensio & Delmas, 2015; Craig, 2016; Craig & Allen, 2015; Delmas et al., 2013; Gillingham et al., 2013; Waechter et al., 2015). This is consistent with the theory of planned behavior (TPB; Ajzen, 1991), which states that awareness and positive attitudes about a topic increase the likelihood of a behavior. In the context of this study, the likelihood of energy saving behaviors would increase when preceded by awareness and positive perceptions about EE programs and / or the IOU providers.

Utility organizations primarily rely on a deemed savings model in residential EE programs, where incentive levels are based on a regulatory-assigned kWh savings value rather than observed savings (Craig & Allen, 2014). Overlooked in the deemed savings model is observed climatic interaction. Similar to volumetric pricing charged to residential customers, electricity savings assigned to electricity efficiency programs is unable to completely capture the increase or decrease in electricity demand related to actual weather conditions (Craig, 2016). As such, EE programs are primarily used as a deterrent to peak electricity demand conditions rather than a real-time response.

The goal of this study was to examine the impact of electricity generation by fuel source type and electricity consumption on carbon emissions to assess the role of climatic variability and energy efficiency (EE) in 48 contiguous United States (US). Accordingly, the study will first examine the impact that electricity generation by fuel source and electricity consumption has on

the GHG CO₂ for the contiguous US. State-level relationships between climatic variability, EE, and residential electricity consumption will then be explored. Further, the variability in residential electricity consumption will be examined in terms of climatic variability and EE. Procedure, methods, and statistical analysis will then be provided, followed by results, theory application, and discussion of findings.

2.2.1 Impact of electricity generation and consumption on GHG emissions

Long-term climatic variability and extreme weather events are influenced by GHG emissions, and are projected to intensify (Craig, 2016; IPCC, 2014; Ingram et al., 2013). Consequently, climatic variability and extreme weather events can increase the demand for electricity. In a longitudinal residential study, temperature-related indices were the strongest indicators for electricity consumption (Jovanovic et al., 2015). In a review of the impact of climate change on electricity markets, Mideksa and Kallbekken (2010) found that electricity demand for cooling is expected to increase and electricity demand for heating is expected to decrease. Increased electricity demand from users, increased population, urbanization, and growing economies have resulted in increased electricity consumption, generation, and GHG emissions (EIA, 2015b; ICPP, 2014; Karanfil & Li, 2015; Quadrdan et al., 2015; Ryu et al., 2014; Schill & Clemens, 2015; Shahiduzzaman & Layton, 2015; Shen et al., 2011).

 CO_2 remains the most influential and harmful GHG related to anthropogenic induced climatic variability (IPCC, 2014), with 81.5% of GHG emissions from electricity production and use attributable to CO_2 (EIA, 2011). Overall electricity consumption and generation have traditionally shared a strong relationship (r = .879, p < .01; EIA 2015a, d) in the US, yet the relative influence on CO_2 emissions that takes into account fuel sources for electricity generation and consumer segments is not widely understood. Electricity generation has historically met

consumer demand needs relying primarily on fossil fuels (Figure 3; EIA, 2015a, d). Natural gas is the fastest growing fuel source in terms of generation, however, more wind generation capacity was added in 2015 relative to other fuel sources (EIA, 2015f). Despite a shift towards cleaner electricity production, there is still a continued reliance on fossil fuels. With the understanding that long-term climatic variability and extreme weather events are positively related to increased generation, consumption, and GHG emissions, a goal of this study is to gain a clearer understanding of the relationship that electricity generation and electricity consumption share with CO₂ emissions. Specifically, we will try to address the following question:

Research question 1: How much of the variability in total US CO₂ emissions is explained by electricity generation and consumption.

2.2.2 Relationship between CDD, HDD, and EE

Climate models predict increased temperature variability, increased electricity demand related to cooling degree days (CDD), and decreased electricity demand related to heating degree days (HDD) absent other factors (IPCC, 2014; McFarland et al., 2015). CDD and HDD are indicators of average daily temperatures that are either higher or lower, respectively, than a predetermined baseline temperature (EPA, 2014). CDD and HDD are used here because they are more reliable indicators of electricity consumption than temperature (Mourshed, 2012). The baseline temperature used for CDD and HDD calculations in the current study was 65° F.

Between 1981 and 2014, CDDs increased throughout the majority of the US (See Figure 4). As CDDs increase, electricity consumption is projected to increase due in large part to the high proportion of electric cooling equipment used in the US (EIA, 2009; McFarland et al., 2015; Mideksa & Kallbekken, 2010).

Studies exploring variability in electricity explained by degree days have shown strong correlations both in the US (r = .84; Quayle & Diaz, 1980) and abroad (r = .56; Yi-Ling et al., 2014) on a localized level. Two salient factors not included in the models that predict positive relationships with electricity consumption and degrees days are efficiencies and shifts in populations (McFarland et al., 2015). A major contribution of the current study is capturing these factors, where electricity consumption and EE savings are calculated per resident for each state. As discussed above, evaluating the effectiveness of EE programs is complicated by the use of deemed, or assigned, electricity savings in addition to the rebound effect (Craig & Allen, 2014; Gilleo et al., 2014; Gillingham et al., 2013). In lieu of deemed electricity savings, annual peak kW electricity reduction from EE per residential ratepayer is used here to capture actual savings. Peak kW reduction allows for changes in actual electricity consumption relative to observed climatic conditions to be examined.

EE programs are perceived as the most cost-effective method to reduce consumption and lower CO₂ and other GHG emissions, and spending on EE programs continues to increase (Gilleo et al., 2014). With changing long-term climatic trends and the increased frequency of extreme weather events (NOAA, 2015), the evaluation of EE programs becomes further convoluted. As such, a goal of the current study is to examine the relative impact that CDD, HDD, and actual peak EE kW savings per resident have on electricity consumption per resident. This was the first study to the authors' knowledge that examined the impact of climate and EE on residential electricity consumption US-wide. Specifically, we will address the following two questions:

Research question 2: How strong are the relationships residential electricity consumption share with CDD, HDD and kW reduction from EE at the state-level?

Research question 3: How much of the variability in residential electricity consumption is explained by CDD, HDD, and kW reduction from EE at the state-level?

2.3 Materials and methods

2.3.1 Procedure and measures

Annual electricity generation, electricity consumption, and CO₂ emissions from raw data for the years 1990 through 2013 were retrieved from the EIA website (EIA, 2015a, c, d). Electricity generation and consumption are reported in megawatt hours (MWH) and CO₂ emissions are reported in metric tons. The daily maximum and minimum temperature on 2.5-min (around 4 km) resolution were both obtained from Di Luzio et al. (2008). The dataset was constructed using the Parameter-Elevation Regressions on Independent Slopes Model and daily observation from more than 7500 weather stations. The annual HDD and CDD on individual grid cell during 1990-2013 were calculated using the daily maximum and minimum temperature. Then the HDD and CDD for each state were averaged using areal weight algorithm. Electricity consumption per resident at the state-level and associated electricity peak kW reduction from EE were calculated from raw data from Form EIA-861 for the years 1992 through 2012 from the EIA website (EIA, 2015e). Only annual data was available for this time period for peak kW reduction from EE programs and residential electricity consumption. Original values and anomalies were calculated for CDD, HDD, and kW reduction from EE. The original values capture the extreme nature of yearly weather conditions and EE savings, and the anomaly values capture the long-term trends over the study period.

The twelve fuel source types for electricity generation include: Biomass MWH, coal MWH, geothermal MWH, hydroelectric MWH, natural gas MWH, nuclear MWH, other MWH, other gas MWH, petroleum MWH, solar MWH, wind MWH, and wood MWH. US-wide

electricity consumption variables include residential MWH, commercial MWH, and industrial MWH. Emissions from electricity generation were reported in metric tons of CO₂. CDD and HDD were the measures used for climatic variability. kWh per residential consumer was the variable used to measure residential electricity consumption at the state-level. Electricity savings from EE programs is reported as the actual peak kW reduction per residential consumer in terms of annual savings (i.e., the lifetime kW savings from all EE participants in current and past years during the reporting period).

2.3.2 Statistical analysis

IBM SPSS Statistics version 23 was used for statistical analysis. Descriptives for US-wide variables are graphed in Figures 1, 2, and 3. Regression analysis using stepwise linear regression was conducted to examine the relationship between CO₂ emissions from electricity generation, electricity generation by fuel source, and electricity consumption by sector (see Table 1 for model). Descriptive statistics were calculated for the kWh electricity consumption per resident, CDD, HDD, kW reduction per resident from EE, and correlations were calculated (Table 2). Regression models were run for each of the lower 48 states using stepwise linear regression. The models examined the variability in kWh consumption per resident explained by CDD, HDD, and kW electricity reduction per consumer. Common to climate studies, anomaly values were also included CDD, HDD, and kW electricity reduction per consumer.

2.4 Results

2.4.1 National results

Research Question 1 explored the relationship that electricity generation and consumption had with CO_2 emissions. A seven-step model emerged explaining 99.6% of the variability in CO_2 emissions from electricity production (Adjusted $R^2 = .996$, p < .0001; F =

914.252, p < .0001). Significant relationships with CO₂ emissions existed for coal MWH generation, residential MWH electricity consumption, industrial MWH electricity consumption, petroleum MWH generation, other gas MWH generation, nuclear MWH generation, and natural gas MWH generation. Table 1 provides detailed results. In the first step, electricity generation from coal explained 83.8% (Adjusted R^2 = .838, p < .0001) of the variability in CO₂ emissions (Standardized β = .751, p < .0001). The second step of the model also included residential electricity consumption and explained an additional 13.4% (Adjusted R^2 = .134, p < .0001) of the variability in CO₂ emissions from the electric industry (Standardized β = .397, p < .0001). No other variable accounted for more than 0.8% of the variability in CO₂.

2.4.2 State-level correlation analysis results

Research Question 2 examined the relationships that CDD, HDD, and kW reduction from EE programs had with kWh electricity consumption per resident. Correlation analysis examined the relationships (see Figure 5). See Table 2 for a full list of correlation values for each variable. CDD has strong positive correlations with electricity consumption throughout the US, with 33 significant relationships. The majority of the US saw negative correlations between HDD and electricity consumption, although only five relationships were significant. Eight states exhibited positive correlations between kW reduction from EE per resident and kWh electricity consumption. The majority of the US demonstrated negative relationships between kW electricity reduction from EE and electricity consumption. 34 states exhibited significant correlations between kW reduction and electricity consumption.

The strongest relationships observed between CDD and electricity consumption were in the Southern and Eastern US, with the strongest correlations in Louisiana (r = .799, p < .001) and North Carolina (r = .835, p < .001). Counterintuitive negative relationships between CDD and

electricity consumption despite an increase in CDD during the study period were exhibited in seven states: Idaho (r = .432, p < .01), Maine (r = .270, p > .1), Montana (r = .10, p > .1), North Dakota (r = .321, p > .1), Oregon (r = .328, p > .1), Vermont (r = .282, p > .1), and Washington (r = .321, p > .1). The five significant relationships between HDD and electricity consumption were in higher latitude states: Colorado (r = .448, p < .01), Idaho (r = .469, p < .01), Michigan (r = .448, p < .01), New Jersey (r = .436, p < .01), and Vermont (r = .767, p < .001).

The strongest negative relationship between kW reduction from EE and electricity consumption was in New Hampshire (r = -.874, p < .001) and the strongest positive relationship in Oregon (r = .830, p < .001). There were eight such positive relationships in the US occurring in the Northwest US (Idaho, North Dakota, Oregon, Washington, Wyoming), the Northeast US (Maine, Vermont), and in Kansas.

2.4.4 State-level regression analysis results

Stepwise linear regression was utilized to examine variability in kWh consumption per resident explained by CDD, HDD, kW reduction per resident from EE, and the respective anomalies. Results from Research Question 3 show that all US states except Maine, Montana, New Mexico, North Dakota, and South Dakota produced significant results (see Table 2 for results from all 48 states). Eight states produced models that explained over 70% of the variability in electricity consumption, including Arizona, Arkansas, Georgia, Michigan, Minnesota, Mississippi, New Hampshire, and New Jersey. Four distinct model types emerged: single-step climatic models, single-step EE models, multi-step climatic and EE models, and non-significant models.

2.4.4.1 Single-step climatic models

The single-step climatic models included eight significant relationships between CDD and electricity consumption with the most variability explained in Oklahoma (Adj. $r^2 = .587$) and Kansas (Adj. $r^2 = .587$). Other states with variability explained by CDD include Colorado, Delaware, North Carolina, Ohio, Tennessee, and Texas. Louisiana (Adj. $r^2 = .681$) and Wisconsin (Adj. $r^2 = .414$) shared significant relationships with the CDD anomaly. Vermont (Adj. $r^2 = .567$) was the only state where with variability in electricity consumption explained by HDD.

2.4.4.2 Single-step EE models

The single-step EE models included 14 states, eight states with variability in residential electricity explained by EE kW savings per residential household anomaly and six explained by the true EE values. The most variability for either of these variables was in New Hampshire (Adj. $r^2 = .752$) followed by Oregon (Adj. $r^2 = .673$) and Pennsylvania (Adj. $r^2 = .661$). Other states with variability explained by the anomaly were California, New York, Virginia, West Virginia, and Wyoming. The most variability explained by the true EE kW savings value per resident was Massachusetts (Adj. $r^2 = .617$) followed by Idaho (Adj. $r^2 = .522$). Other states with variability explained by the true value include Florida, Maryland, Nevada, and Utah.

2.4.4.3 Multi-step mixed climatic and EE models

There were 18 states where variability in residential electricity consumption was explained by a model that included both climatic and EE variables. The mixed models were the most predictive as a group. Ten states had the majority of variability in electricity consumption by the EE kW savings anomaly where CDD anomaly was the second factor in six states (Arizona, Arkansas, Illinois, Michigan, Missouri, Rhode Island), the HDD anomaly was the

second factor in two states (Alabama, Washington), and the true value for CDD was the second factor in two states (Connecticut, Iowa). The two strongest relationships were explained by EE kW savings anomalies and CDD anomalies in Arizona (Adj. $r^2 = .617$) and Arkansas (Adj. $r^2 = .756$). Only Minnesota had a model with the majority of variability explained by the actual EE kW savings value in combination with CDD (Adj. $r^2 = .706$). Two step models that included CDD and EE kW savings emerged in Georgia (Adj. $r^2 = .751$) and in Nebraska (Adj. $r^2 = .472$). Led by the anomaly for CDD followed by EE kW savings, two step models emerged in Indiana (Adj. $r^2 = .602$), Kentucky (Adj. $r^2 = .610$). Likewise, two step models that included the anomaly for CDD followed by the anomaly for EE kW savings emerged in Mississippi (Adj. $r^2 = .746$) and New Jersey (Adj. $r^2 = .707$). Lastly, a lone three step model emerged in South Carolina that and explained 68.4% of the variability in electricity consumption that included CDD (Adj. $r^2 = .483$), the anomaly for EE kW savings (Adj. $r^2 = .112$), and the anomaly for HDD (Adj. $r^2 = .089$).

2.5 Application of theory

Results from this study demonstrate the salient role that residential electricity consumers have on GHG emissions, and also the relative ineffectiveness of utility programs across the majority of the US to mitigate residential consumption. Where negative relationships exist between residential electricity consumption and EE kW savings, the general trend in the US over the study period is for savings to decrease per resident as consumption increases. Allcott and Mullainathan (2010) contend that non-economic incentives can be just as powerful as economic incentives common with utility EE programs at influencing pro-conservation behaviors (Craig & Allen, 2014; Gilleo et al., 2014). Craig and Allen (2015) suggest a holistic approach that encompasses both behavioral and economic considerations. Results from Delmas et al. (2013)

support this notion, where electricity consumption increased when incentives for EE did not include rich feedback. Absent mechanisms to change behaviors, such as TPB messaging, a rebound effect can occur where deemed savings are not realized, persistence of actual electricity savings is not maintained, and in some cases, electricity consumption actually increases (Asensio & Delmas, 2015; Delmas et al., 2013; Greening et al., 2000).

The TPB contends that awareness, attitudes, perceived behavioral control, normative influence, and intentions precede actual behaviors (Ajzen, 1991; Armitage & Connor, 2001). Several recent studies demonstrated the influence that TPB could have on behaviors and behavioral intentions related to energy conservation (e.g., Abrahamse & Steg, 2011; Brosh et al., 2014; Chen, 2016; Craig, 2016; Lynch & Martin, 2013). Specific to EE programs, Craig (2016) found there were significant differences in residential participation in EE programs and support for EE subsidies based on awareness about EE programs. Lynch and Martin (2013) observed actual electricity savings by over 5% in a longitudinal study that included a control group that received communications that drew from the TPB. Brosh et al. (2014) explained 34% of the variability in energy-saving behavior based on TPB inputs with residents. Behavioral control and attitudes are both predictive of intentions to conserve energy (Abrahamse & Steg, 2011; Lo et al., 2015).

Residential electricity consumers lack knowledge about electricity markets and about EE, are charged relatively low fixed rates for electricity, and spend a small portion of their income for electricity (Bresler et al., 2013; Craig & Allen, 2014; Langevin et al., 2013). Misinformation and previously formed attitudes can deter the receipt of new information and solidify negative attitudes that can deter positive behaviors. Despite billions of dollars in incentives for EE programs expended across the US annually (Gilleo et al., 2014), increasing residential electricity

consumption in the US suggests more needs to be done. Responsive behavioral-focused programs with rich feedback have quantifiably demonstrated electricity reduction by over 15% and GHG reduction by up to 8% (Craig & Allen, 2015; Kopsakangas-Savolainen, 2015). Communication mechanisms such as feedback and messaging are crucial, and can encourage positive attitudes about EE and / or the utility organization and gives residents a sense of behavioral control; this has been shown to result in intentions to conserve electricity, actual conservation behaviors, and a persistence of savings over time (Ajzen, 1991; Abrahamse & Steg, 2011; Asensio & Delmas, 2015; Brosh et al., 2014; Chen, 2016; Craig & Allen, 2015; Craig & Allen, 2014; Fisher & Newell, 2008; Lynch & Martin, 2013).

2.6 Discussion

This study sought to better understand electricity generation by fuel source type and residential electricity consumption while controlling for inter-year climatic variability, long-term climatic trends, and kW reduction from EE programs. Utility organizations face regulatory pressures, policy concerns, and mandated kW savings goals while avoiding participation in EE programs that occurs by chance or without influence (Craig & Allen, 2014; Haeri & Khawaja, 2012; Spence et al., 2015). Despite billions of dollars spent to reduce electricity consumption in the US (Gilleo et al., 2014), the majority of utility organization electricity generation comes from coal, which is the most salient contributor to CO₂ emissions from electricity production (EIA, 2015a). It is important for regulatory bodies with oversight of utility organizations to ask how realistic, consistent, and / or attainable EE savings goals are in light of the mixed and / or negative results of EE program effectiveness demonstrated here. Climatic variability and decreased EE savings per resident were both salient predictors of increased electricity consumption in this study. Regulators may be better suited to encourage successful programs to

continue while discouraging unsuccessful programs than continuing with the status quo and use of a deemed savings model (Allcott & Mullainathan, 2010).

2.6.1 National outlook

Nationally, the US produces four times more CO₂ per resident than the largest electricity consumer in the world, China (EIA, 2015b). The results from Research Question 1 support previous research that energy organizations reliant on fossil fuels for generation produce the majority of the world's CO₂ (Heede, 2014) and that GHG emissions are anthropogenic driven (IPCC, 2014). Across the US, a seven-step model explained 99.6% of the variance in CO₂ emissions from overall electricity generation, with 83.8% of the variance explained by electricity generated from coal and 13.4% by residential electricity consumption.

Salient relationships between commercial and industrial electricity consumption with CO₂ emissions were not present, further solidifying the residential sector as the focal group in the study. Emissions are projected to increase upwards of 17% in the residential sector by 2020 (Langevin et al., 2013), highlighting the need to reduce consumption from fossil fuel sources and to shift to cleaner energy infrastructure. Technologies to reduce and capture GHG emissions related to fossil fuel electricity generation offer a potential solution (e.g., Brouwer et al., 2015; Hanak et al., 2015; Sanna et al., 2015). However, a recent life-cycle assessment of energy infrastructure "suggests that an electricity supply system with a high share of wind energy, solar energy, and hydropower would lead to lower environmental impacts than a system with a high share of CCS [carbon capture sequestration]" (Hertwich et al., 2015, p. 6281). Hertwich et al. is supported in practice in the US. In 2015 the largest new electricity generation fuel source was wind, and there was a reduction in electricity generation from coal (EIA, 2015f).

Results from Research Question 2 provide a few overarching findings about relationships across the US between residential kWh consumption, CDD, HDD, and kW reduction from EE programs. The vast majority of the US experienced positive relationships between kWh consumption per resident and CDD. The majority of the US also experienced negative relationships between kWh consumption per resident and HDD. With the observed increase in CDD in this study (see Figure 5) and the projected increase in CDD in the future (Ingram et al., 2013; IPCC, 2014), the impact of climatic conditions on electricity consumption cannot be understated. Research Question 2 also examined the relationship between kWh consumption per resident and kW reduction from EE programs. The majority of states demonstrated negative relationships between kWh consumption per resident and kW reduction. There were counterintuitive relationships in seven states where a negative relationship between CDD and residential consumption was exhibited and where a positive relationship between kW reduction from EE and residential consumption was exhibited. A state-level outlook is provided in the following section to better understand localized correlation trends and the counterintuitive relationships that emerged.

Research Question 3 used stepwise regression approach to understand the variability in kWh consumption per resident explained by CDD, HDD, and EE kW savings for each state. Actual values and anomaly values are provided for each dependent variable to help determine whether short-term variability or long-term trends are influencing electricity consumption. The variability in 25 states was explained by a single-step regression model where climatic models were primarily driven by actual CDD and EE models were mixed between actual and anomaly values. 18 states exhibited multi-step climatic and EE models, and five states did not exhibit significant relationships with kWh consumption per resident.

2.6.2 State-level outlook

EE programs are primarily regulated at the state-level and the effectiveness of EE programs vary widely from state-to-state (Craig & Allen, 2014; Gilleo et al., 2014). Despite similarities in climatic conditions regionally in the US, the single and multi-step models in Table 2 show that that widespread trends largely do not exist. At the state-level, however, interesting findings emerge about the role that climatic conditions, EE programs, and a mix of both can have on residential electricity consumption.

2.6.2.1 Single-step climatic models

The actual value for CDD positively explained variability in residential electricity consumption in eight of the 11 states for the single-step climatic models (see Table 2). The actual value is a measure of the variability of CDDs from year-to-year, and captures more extreme years in the study period. The anomaly values for CDD explained the variability in residential electricity consumption in two states, Louisiana and Wisconsin. The strongest relationship of the climatic models was in Louisiana, where 68.1% of the variability in electricity consumption was explained by the anomaly for CDD. Vermont, the state with the second highest average HDD value, was the only state where variability in consumption was explained by HDD. Vermont experienced a decrease in HDD that coincided with a decrease in consumption. The strong positive relationship between HDD and consumption here provides a plausible explanation for the negative correlation found between CDDs and consumption in Vermont. With CDD values and extreme events both projected to increase (Ingram et al., 2013; IPCC, 2014; McFarland et al., 2015), the short- and long-term impact of climatic and extreme conditions on electricity consumption are of interest to utility organizations tasked with meeting demand conditions while adhering to state and federal regulations.

2.6.2.2 Single-step EE models

For the single-step EE models, six states had variability in residential electricity consumption explained by actual kW reduction. Florida, Maryland, Massachusetts, Nevada, and Utah all experienced negative relationships between kW reduction from EE and electricity consumption. That is, an increase in kW reduction from EE coincided in a decrease in electricity consumption and vice-versa. In Idaho, however, there was a positive relationship where kW reduction from EE significantly explained the variability in consumption. Initially, increases in kW reduction coincided with increased consumption Idaho, then the two variables decreased together throughout the study period. The correlation analysis in Idaho showed a counterintuitive negative relationship between consumption and CDD. The results from regression analysis suggest that this negative relationship is explained by kW reduction from EE programs rather than the relationship between CDD and consumption.

Eight states had variability explained by the kW reduction from the EE anomaly. Similar to the actual kW reduction values, negative relationships emerged in California, New Hampshire, Pennsylvania, Virginia, and West Virginia. Positive relationships emerged in Oregon and Wyoming. Oregon and Wyoming are also two states where a negative correlation was present between CDD and electricity consumption. Similar to Idaho, kW reduction and electricity consumption decreased together throughout the study period in Oregon. In Wyoming, however, variability in electricity consumption was positively explained by an increase in long-term kW reduction. The kW reduction levels were nominal per consumer, and the results from the correlation analysis where a counterintuitive relationship emerged were not significant.

The implications of the findings for the single step EE models are of great interest to both regulators and utility organizations. Research Question 1 developed electricity generation from

coal and residential electricity consumption as the two most salient contributors to CO₂ emissions during the study period. However, the vast majority of the states saw an increase in electricity consumption as kW reduction from EE programs (both actual and anomaly values) decreased throughout the study period. Persistence of decreased electricity consumption did not occur in the majority of states. The two exceptions were in Idaho and Oregon. Previous research indicates the utilization of behavioral interventions, such as the use of environmental messaging campaigns or feedback mechanisms to decrease consumption, as part of EE programs by utility organizations during the study period was nominal (Craig & Allen, 2014). A rebound effect has been found where residential electricity consumption increases when EE programs are deployed absent rich feedback mechanisms (Delmas et al., 2013; Gillingham et al., 2013). To help realize long-term reductions in residential electricity consumption, it is important to integrate behavioral mechanisms consistent with the TPB to increase knowledge and positive perceptions about EE efforts (Craig & Allen, 2015; Ajzen, 1991).

2.6.2.3 Multi-step mixed climatic and EE models

McFarland et al. (2015) note that many of the climate models used to forecast electricity demand do not account for EE savings. A major contribution of the current study is the emergence of historical regression models that account for both climatic indicators as well as efficiency efforts. As a group, the multi-step models explained more variability in electricity consumption than single-step models. Multi-step mixed models emerged in 18 states, where the kW reduction from EE anomaly explained the majority of variability in residential electricity consumption in 10 states. The variability in consumption was negatively explained by the EE anomaly in all but one of these states; Washington shared a positive relationship. Similar to Oregon and Idaho, Washington is a Northeastern state that demonstrated a negative correlation

between CDD and consumption. Consistent with Oregon, the long-term trend in kW from EE decreased throughout the study period as consumption decreased in Washington. Six of the 10 states included the CDD anomaly as the second step in the model. All relationships with the CDD anomaly were positive, with an increase in CDD explaining the increase in electricity consumption. The actual value for CDD was present as the second step in Connecticut and Mississippi. A negative relationship based on inter-year variability of CDD emerged in both states. Albeit weak, relationships with the HDD anomaly were present in Alabama and Washington. The actual value of kW reduction from EE was the first step of a model that also included the actual value for CDD, and the relationships were negative and positive, respectively.

Seven multi-step models mixed models included climatic variables in the first step. Four of these models included the CDD anomaly in the first step and three included the actual value of CDD in the first step. In all instances, the CDD value positively explained the variability in residential electricity consumption. The second step was mixed between actual and anomaly values for kW reduction from EE programs. Whether short-term variability or long-term trend, all EE values negatively explained the variability in consumption. South Carolina was the only state where a three-step model occurred. The HDD anomaly positively explained 8.9% of the variability in consumption in the final step.

2.6.3 Limitations and future research

This study is not without limitation. Information asymmetry by utility organizations was a salient limitation. For instance, for the electricity generation, emissions, and electricity consumption data (EIA, 2015a, c, d), information was provided annually. Additionally, EE data and residential consumption from Form EIA – 861 (EIA, 2015e) was provided on an annual

basis. EIA – 861 had other problems. There were instances where utility organizations reported EE data for multiple states. In these cases, data were omitted because they could not be accurately assigned to a state. Further, the study relied on peak kW reduction instead of deemed savings. kW reduction captures electricity taken off the grid and permits climatic interaction (i.e., hotter days more electricity generation will be needed) to be examined. However, it does not capture behavioral aspects of states engaged in feedback-driven, transformation-focused EE efforts.

Future research should examine the daily and / or monthly interaction between electricity generation, residential electricity consumption, and climatic indicators. A state-by-state approach should be employed similar to the approach here, and will provide a clearer picture of how electricity is consumed and generated within and among states. States that have successfully deployed EE programs that decreased residential electricity consumption, including Idaho, Oregon, and Washington, should be examined as possible models for successful deployment of initiatives, including behavioral interventions and messaging content. Currently, climatic risk factors related to electricity generation and consumption are not well-defined. This study provided an overview of the US and the relationships between consumption, generation, and emissions. Moving forward, climate models can be generated to quantify climatic risk to electricity generation and consumption that also considers population and EE efforts. Furthermore, with federal legislation outstanding for utility organizations to reduce carbon emissions, it is feasible that electricity production with fossil fuels could continue in states while clean energy is imported to meet regulatory obligations. Future research can examine the fuel source mix in each state in terms of both generation and consumption.

2.6.4 Conclusion

Extreme weather events and increased CDDs are expected to increase across the US, increasing the demand for electricity absent other factors such as EE efforts (IPCC, 2014; McFarland et al., 2015; NOAA, 2015). Climatic relationships in the current study support these findings. Climatic relationships were largely dominated by CDD and CDD anomaly values, where the increase in CDD positively explained the increase in residential electricity consumption. The majority of states experienced a decrease in HDDs, however, the only state where HDD was included in the first-step of a model was in Vermont. This relationship does, however, support previous models that predict electricity demand will decrease with decreased HDDs. The Southern US is particularly vulnerable to increased temperature due to high kWh consumption and reliance on electric heating and cooling equipment (EIA, 2015d; EIA, 2009). The strong correlations with CDD in Southern US suggest the importance of mitigation strategies, particularly in light of the reliance of fossil fuels for electricity generation in the region (EIA, 2015a). The need for utility organizations and regulators to quantify the impact of climatic conditions is inherent in this body of research.

In the vast majority of states where short-term or long-term kW reduction from EE was present, a negative relationship existed. This indicates that when EE efforts were enacted, reduction in residential electricity consumption followed. However, most states saw a gradual decrease in residential EE kW reduction while electricity consumption steadily rose. This negative relationship suggest the use of EE programs to respond to electricity demand instead of transforming the manner in which electricity is consumed. A potentially successful model for deployment for EE programs may be presented in the Northeast US. Idaho, Oregon, and Washington all demonstrated higher levels of kW reduction from EE early in the study period,

and saw kW reduction per resident and electricity consumption per resident gradually decrease. Cropp et al. (2014) note that Energy Trust, a non-profit organization, manages efficiency programs for four utility organizations in Oregon. Administered by an outside group, the profit-seeking behavior of publicly held entities becomes irrelevant, credibility increases, and the motives to effectively communicate and deploy EE programs have the potential to improve.

Currently, the continued increase in consumption in the US is closely related to increased electricity generation that relies on GHG emitting fossil fuels. This study suggest that electricity generated from coal is most strongly related to CO₂ emissions from electricity production, and residential consumption had the second most salient relationship with emissions. Despite billions of dollars for electricity EE programs, results suggest that EE programs are not accurately quantifying the climatic impact on electricity consumption. Of great concern, utility organization commitment to and deployment of residential EE programs is also highlighted. Bansall and Clelland (2004) noted that environmentally legitimate behaviors are those that are proper, appropriate, and desirable. Accountability and credibility are integral for utility organizations to act legitimately, particularly when the organizations deploy EE programs (Allen, 2016; Alrazi et al., 2015). Looking forward, utility organizations and regulators alike can utilize the findings in the study to better understand how electricity generation and consumption are impacted by short-term climatic variability, long-term climatic trends, and EE programs in an effort to reduce GHG emissions and the related environmental impact.

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2.8 Figures

Figure 1. Megawatt hour electricity generation for top fuel sources between 1990 and 2013.

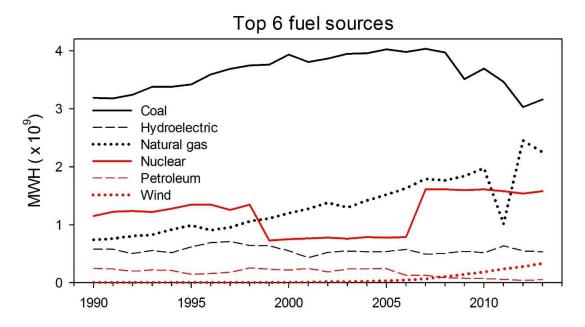


Figure 2. Megawatt hour electricity consumption by sector between 1990 and 2013.

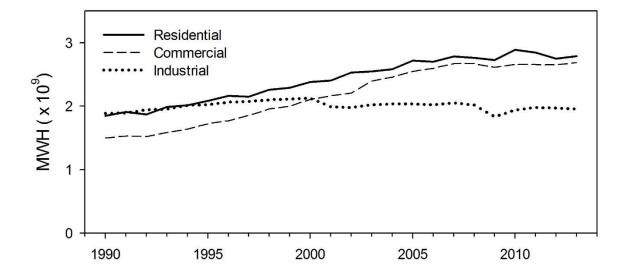


Figure 3. Overall megawatt hour electricity generation and consumption between 1990 and 2013 for the contiguous US.

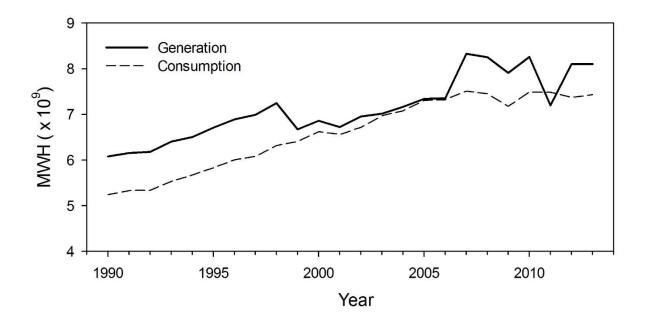
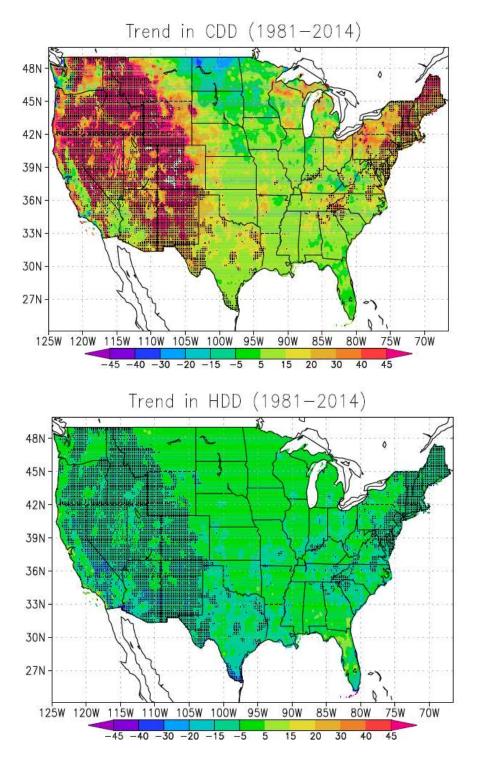
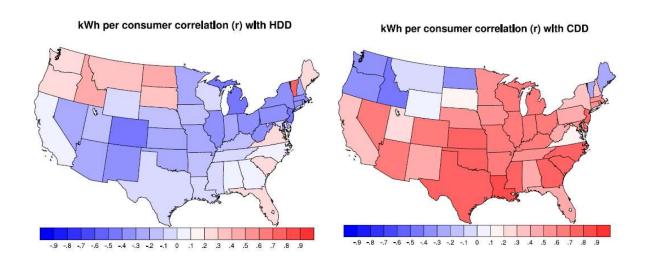


Figure 4. Cooling degree days and heating degree days between 1981 and 2014.



Note. Time-series difference tests were run with daily CDD and HDD values. Significant findings from 1981 until 2014 at the p < .01 level are shaded.

Figure 5. Spatial maps of correlation between kWh consumption per consumer and CDD, HDD, and kW electricity reduction per consumer.



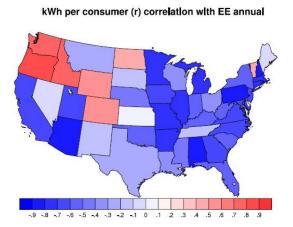


Table 1. Stepwise linear regression analysis for CO_2 by generation fuel source type and electricity consumer sector.

Step and variables	В	SE	β	t	p
Step 1 ($AdjR^2 = .838$)					
CoalMWH	1.117	.102	.919	10.950	.000****
Step 2 $(AdjR^2 = .972)$					
CoalMWH	.912	.047	.751	19.451	.000****
ResMWH	.444	.043	.397	10.298	.000****
Step 3 $(AdjR^2 = .980)$					
CoalMWH	.811	.050	.667	16.100	.000****
ResMWH	.479	.038	.429	12.743	.000****
IndMWH	.638	.200	.120	2.48	.005**
Step 4 $(AdjR^2 = .989)$					
CoalMWH	.676	.051	.556	13.260	.000****
ResMWH	.652	.052	.584	12.743	.000****
IndMWH	.691	.152	.130	4.552	.001**
PetrMWH	.890	.223	.168	3.986	.001**
Step 5 $(AdjR^2 = .992)$					
CoalMWH	.676	.042	.556	16.043	.000****
ResMWH	.645	.043	.577	15.005	.000****
IndMWH	.950	.150	.179	6.318	.000****
PetrMWH	.879	.185	.166	4.760	.000****
OtherGasMWH	-8.995	2.875	075	-3.128	.006**
Step 6 $(AdjR^2 = .995)$					
CoalMWH	.719	.035	.591	20.830	.000****
ResMWH	.527	.046	.471	11.397	.000****
IndMWH	.946	.116	.178	8.169	.000****

Table 1. Stepwise linear regression analysis for CO₂ by generation fuel source type and electricity consumer sector (continued).

Step and variables	В	SE	β	t	p
PetrMWH	.876	.142	.166	6.155	.000****
OtherGasMWH	-9.456	2.219	079	-4.261	.001**
NatGasMWH	.086	.024	.108	3.649	.002**
Step 7 $(AdjR^2 = .996)$					
CoalMWH	.713	.031	.587	23.214	.000****
ResMWH	.509	.042	.456	12.201	.000****
IndMWH	.953	.103	.179	9.263	.000****
PetrMWH	.630	.164	.119	3.840	.001**
OtherGasMWH	-10.092	2.219	084	-5.072	.000****
NatGasMWH	.083	.021	.104	3.967	.001**
NuclMWH	057	.024	050	-2.354	.032*

Note. * = p < .05, ** = p < .01, *** = p < .001, **** = p < .000. The electricity generation abbreviations by fuel source and electricity consumer are as follows: Coal electricity generation (CoalMWH), residential electricity consumption (ResMWH), industrial electricity consumption (IndMWH), petroleum electricity generation (PetrMWH), other gas electricity generation (OthGsMWH), natural gas electricity generation (NatGMWH), and nuclear electricity generation (NuclMWH).

Table 2. Descriptives, correlations, and regression outputs.

Single.	kWh	CDD	HDD	EE	CDD/kWh	HDD/kWh	EE/kWh	Adj.R	2 Step1 Step2 Step3	Standardized Beta
on gre	Step Clin	natic Mod	lels							
CO DE KS LA NC OH OK TN TX VT	7948 10985 10561 14785 13087 10165 12743 15329 13840 7133 8532	243 669 765 1455 831 441 1059 758 1410 143 236	4117 2461 2818 1008 1896 3193 2025 2158 1271 4597 4459	4.52 n/a .076 .097 17.23 5.26 7.19 .51 45.79 21.68 25.27	.660 .773 .835 .799 .631 .780 .557 .773 282	448 246 259 031 .073 360 226 022 076 .767 092	410 n/a .057 335 625 380 508 129 297 .440 327	.437 .405 .576 .681 .619 .366 .587 .274 .576 .567 .414	CDD = .437 CDD = .405 CDD = .576 CDDA = .681 CDD = .619 CDD = .366 CDD = .587 CDD = .274 CDD = .576 HDD = .567 CDDA = .414	Std. β = .682, p < .01; F = 16.506, p < .01 Std. β = .660, p < .01; F = 14.630, p < .01 Std. β = .773, p < .001; F = 28.129, p < .00 Std. β = .835, p < .001; F = 33.463, p < .00 Std. β = .631, p < .01; F = 33.463, p < .00 Std. β = .631, p < .01; F = 12.570, p < .01 Std. β = .780, p < .001; F = 29.446, p < .00 Std. β = .773, p < .001; F = 28.203, p < .00 Std. β = .773, p < .001; F = 28.203, p < .00 Std. β = .666, p < .01; F = 15.138, p < .01
Single-	Step EE .	Models								
CA 66 FL 13 ID 13 MD 12 MA 72 NV 11 NH 71 NY 66 OR 12 PA 95 UT 88 VA 13 WV 12 WY 99	3591 3041 2295 204 3345 332 325 2304 315 816 3137 2344	750 1749 141 650 287 403 169 227 144 300 396 618 375 142	2030 494 4446 2550 3532 3340 4423 4034 3639 3521 3595 2434 3010 4760	21.07 6.08 7.63 2.65 8.68	.473 452 .523 .533 .679 .362 .344 328 .471 .297 .189	.021 .202 .469 .065 .329 .213 .269 .356 .216 .393 .112 .297 .331 .075	654 518 .739 670 797 021 874 541 .830 813 628 679 583 .520	398 230 522 419 617 433 .752 255 673 .661 362 432 305 232	EEA = .398 EE = .230 EE = .522 EE = .419 EE = .617 EE = .419 EEA = .752 EEA = .255 EEA = .661 EE = .362 EEA = .432 EEA = .305 EEA = .232	Std. β =654, p < .01; F = 14.207, p < .01 Std. β =518, p < .01; F = 6.691, p < .05 Std. β =739, p < .01; F = 22.862, p < .001 Std. β =739, p < .01; F = 15.452, p < .001 Std. β =797 p < .001; F = 33.155, p < .001 Std. β =874, p < .001; F = 16.262, p < .001 Std. β =874, p < .001; F = 61.759, p < .00 Std. β =841, p < .005; F = 7.843, p < .05 Std. β =830, p < .001; F = 42.179, p < .00 Std. β =813, p < .001; F = 37.072, p < .00 Std. β =628, p < .01; F = 12.349, p < .01 Std. β =633, p < .01; F = 16.225, p < .01 Std. β =533, p < .01; F = 9.783, p < .01 Std. β =533, p < .05; F = 7.029, p < .05
State	kWh	CDD	HDD	EE	CDD/kWh	HDD/kWh	EE/kWh	Adj.R2	2 Step1 Step2 Step3	Standardized Beta
Multi-	Step Mixe	ed-Models								
AL 14										
	1578	1099	1454	9.17	.402	.040	802	.695	EEA = .625	Std. β =890, p < .001
		1099 1083	1454 1883	9.17 54.90		.040 272	802 810	.695 .774	HDDA = .070 EEA = .637	Std. β = .299, p < .05; F = 34.309, p < .001 Std. β =686, p < .001
AZ 12	2325				.610				HDDA = .070 EEA = .637 CDDA = .137 EEA = .561	Std. β = .299, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = .396, p < .01; F = 35.266, p < .001 Std. β = .590, p < .001
AZ 12 AR 12	2325 2581	1083	1883	54.90	.610 .691	272	810	.774	HDDA = .070 EEA = .637 CDDA = .137 EEA = .561 CDDA = .215 EEA = .494	Std. β = .299, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = .396, p < .01; F = 35.266, p < .001 Std. β = .590, p < .001 Std. β = .476, p < .01; F = 31.912, p < .001 Std. β = .628, p < .001
AZ 12 AR 12 CT 87	2325 2581 737	1083 1042	1883 1854	54.90 .693	.610 .691 .554	272 138	810 764	.774 .756	HDDA = .070 EEA = .637 CDDA = .137 EEA = .561 CDDA = .215 EEA = .494 CDD = .153 CDD = .546	Std. β = .299, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = .396, p < .01; F = 35.266, p < .001 Std. β = .590, p < .01; F = 31.912, p < .001 Std. β = .628, p < .001 Std. β = .413, p < .01; F = 20.564, p < .001 Std. β = .599, p < .001
AZ 12 AR 12 CT 87 GA 13	2325 2581 737 8069	1083 1042 336	1883 1854 3366	54.90 .693 19.43	.610 .691 .554 .754	272 138 312	810 764 721	.774 .756 .647	HDDA = .070 EEA = .637 CDDA = .137 EEA = .561 CDDA = .215 EEA = .494 CDD = .153 CDD = .546 EE = .205	Std. β = 2.99, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = 3.96, p < .01; F = 35.266, p < .001 Std. β = .590, p < .001 Std. β = .476, p < .01; F = 31.912, p < .001 Std. β = .628, p < .001 Std. β = .413, p < .01; F = 20.564, p < .001 Std. β = 5.99, p < .001 Std. β = .591, p < .001 Std. β = .481, p < .01; F = 25.07, p < .001 Std. β = .482, p < .01; F = 25.07, p < .001
AZ 12 AR 12 CT 87 GA 13	2325 2581 737 8069	1083 1042 336 1128	1883 1854 3366 1327	54.90 .693 19.43 10.15	.610 .691 .554 .754	272 138 312 .041	810 764 721 674	.774 .756 .647	HDDA = .070 EEA = .637 CDDA = .137 EEA = .561 CDDA = .215 EEA = .494 CDD = .153 CDD = .546 EE = .205 EEA = .484 CDDA = .212 CDDA = .389	Std. β = .299, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = .396, p < .01; F = 35.266, p < .001 Std. β = .590, p < .01; F = 31.912, p < .001 Std. β = .476, p < .01; F = 31.912, p < .001 Std. β = .413, p < .01; F = 20.564, p < .001 Std. β = .599, p < .001 Std. β = .598, p < .01 Std. β = .528, p < .01 Std. β = .501, p < .01; F = 19.748, p < .001 Std. β = .573 p < .01
AZ 12 AR 12 CT 87 GA 13 IL 87 IN 11	2325 2581 237 26069 714	1083 1042 336 1128 583	1883 1854 3366 1327 3097	54.90 .693 19.43 10.15 1.13	.610 .691 .554 .754 .697	272 138 312 .041 382	810 764 721 674 714	.774 .756 .647 .751	HDDA = .070 EEA = .637 CDDA = .137 EEA = .561 CDDA = .215 EEA = .494 CDD = .153 CDD = .546 EE = .205 EEA = .484 CDDA = .212 CDDA = .389 EE = .213 EEA = .367	Std. β = 2.99, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = 3.96, p < .01; F = 35.266, p < .001 Std. β = .590, p < .001 Std. β = .628, p < .001 Std. β = .628, p < .001 Std. β = .628, p < .001 Std. β = .99, p < .001 Std. β = .99, p < .001 Std. β = .90, p < .001 Std. β = .528, p < .01; F = 25.07, p < .001 Std. β = .501, p < .01; F = 19.748, p < .001 Std. β = .573 p < .01 Std. β = .478, p < .01; F = 16.13, p < .001 Std. β = .525 p < .01
AZ 12 AR 12 CT 87 GA 13 IL 87 IN 11 IA 10 KY 13	2325 2581 737 8069 714 1659	1083 1042 336 1128 583 527	1883 1854 3366 1327 3097 3084	54.90 .693 19.43 10.15 1.13 4.81	.610 .691 .554 .754 .697 .648	272 138 312 .041 382 288	810 764 721 674 714 567	.774 .756 .647 .751 .696	HDDA = .070 EEA = .637 CDDA = .137 EEA = .561 CDDA = .215 EEA = .494 CDD = .153 CDD = .546 EE = .205 EEA = .484 CDDA = .212 CDDA = .389 EE = .213 EEA = .367 CDD = .143 CDDA = .368	Std. β = .299, p < .05; F = 34.309, p < .001 Std. β = .686, p < .001 Std. β = .396, p < .001; F = 35.266, p < .001 Std. β = .590, p < .001 Std. β = .476, p < .01; F = 31.912, p < .001 Std. β = .428, p < .001 Std. β = .413, p < .01; F = 20.564, p < .001 Std. β = .599, p < .001 Std. β = .599, p < .001 Std. β = .528, p < .01; F = 25.07, p < .001 Std. β = .501, p < .01; F = 19.748, p < .001 Std. β = .573 p < .01 Std. β = .573 p < .01 Std. β = .525 p < .01 Std. β = .542 p < .05
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Table 2. Descriptives, correlations, and regression outputs (continued).

State	kWh	CDD	HDD	EE	CDD/kWh	HDD/kWh	EE/k	Wh A	Adj.R2	Step1	Step2	Step3	Standardized Beta
SC 14	092	1081	1458	31.7	5 .714	.240	587	.(684	CDD = .483	EEA =		Std. $\beta = .519$, $p < .01$ Std. $\beta = .481$ $p < .01$ $\alpha = .089$
WA 13	150	144	3715	6.87	321	.266	.798	.(686	EEA = .617	HDDA	= .059	Std. β = .324, p < .05; F = 15.404, p < .001 Std. β = .804, p < .001 Std. β = .284, p < .05; F = 22.822, p < .001
Non-Si	ignifican	t Models											
ME MT NM ND SD	6264 9753 6983 12646 11421			17.31 18.63 .096 7.18 1.06	270 051 .411 311 .112	.353 387 .413	096 294 106 .425 183	ns ns ns ns					

Note. Kilowatt hour (kWh) electricity consumption is the mean value of consumption between 1992 and 2012 per resident for each state. Cooling degree day (CDD) and heating degree day (HDD) are the average number of days between years 1992 and 2012. Energy efficiency kW reduction is the average savings between 1992 and 2012 per resident in each state and the values in the regression model is denoted by "EE." CDD/kWh, HDD/kWh, and EE/kWh are correlations (r) for the variables. Results from the regression analysis provide the overall adjusted r² value for the model, and the r² for each variable included in the model is included in the steps. The standardized beta values and F-values are for the last step of each regression model. Anomalies (A) were included in the regression analysis for each state. The "n/a" for Delaware indicates there were no EE savings figures provided from the EIA data source. The "ns" indicates that results from the regression analysis were not significant.

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3.1 Abstract

This study examined the interaction between climatic variability and residential electricity consumption in a Southeast US state. Residential electricity consumers were surveyed to better understand how to diffuse positive attitudes and behaviors related to energy efficiency (EE) into households. The study found that 16.8% of the variability in residential electricity consumption for heating applications was explained by indirect EE costs. 36.6% of the variability in residential electricity consumption for cooling applications was explained by indirect EE costs and cooling degree days (CDD). A survey of 2,450 residential electricity consumers was analyzed using the theory of planned behavior (TPB). Significant findings suggest that those residents are aware of utility EE programs are more likely to participate, view utility company motives more favorably, to support governmental subsidies for EE programs, and to support the use of clean energy by utility companies.

Chapter 3: Energy consumption, energy efficiency, and consumer perceptions: A case study for the Southeast United States

3.2 Introduction

With the understanding that the energy consumptive patterns in the United States (US) are a contributing factor to anthropogenic climate change (IPPC, 2014), this study seeks to gain a comprehensive understanding of the relationship between energy consumption, energy efficiency (EE), climate variability, and residential electricity consumer perceptions in the Southeast United States (US). According to the US Energy Information Administration (EIA), the US is among the highest per capita consumers of electricity in the world, using approximately four times as much electricity as the most consumptive country in the world, China. Carbon emissions continues to rise at historic rates, with emissions more than doubling since 1986 (Heede, 2014). According to Heede (2014), emissions are largely driven by fossil fuel and cement producers, with only 90 such companies responsible for over 60% of global carbon emissions since the Industrial Revolution. As the largest electricity consuming sector, particularly in the Southeast US where states are more reliant on fossil fuels and per capita usage is higher than other regions in the US (EIA, 2015), residential consumers are a salient driver of carbon emissions related to the production of electricity. In order to ensure continued, secure energy access and lowered reliance on carbon rich fossil fuel sources, short- and long-term regulatory practices are needed to achieve production and emissions goals in the energy markets (Wang & Tian, 2015).

The evaluation of energy mix is of great concern. Both in the US and in other industrialized countries globally (Heede, 2014; Zhao et al., 2014), fossil fuel reliant energy producers continue to contribute GHG emissions at higher rates than other groups. While the percentage of fossil fuels in the US and abroad in terms of percentage energy mix has decreased

(Haerer & Pratson, 2015; Ryu et al., 2014), issues such as increased electricity demand from non-traditional users (e.g., transportation), increased economic activity, population growth, and energy security have resulted in increased consumption and continued reliance on fossil fuels (Karanfil & Li, 2015; Quadrdan et al., 2015; Ryu et al., 2014; Schill & Clemens, 2015; Shahiduzzaman & Layton, 2015). A host of technologies are available to reduce GHG emissions beyond those traditionally deployed with varying degrees of cost-effectiveness (e.g., Brouwer et al., 2015; Hanak et al., 2015; Sanna et al., 2015). However, there has been some reluctance among residents around the world to embrace clean energy sources and efficiencies in their own homes largely due to lack of awareness (Craig & Allen, 2014; Hanimann et al., 2015; Liu et al., 2015). To further policy and practice, particularly around cost-effective methods to reduce consumption and emissions, the engagement of residential energy users is crucial.

Residential energy use is expected to increase carbon emissions for the sector from 17% to 21% in the US by the year 2020 (Langevin et al., 2013), magnifying the implications of rising emission levels relative to energy producers. According to Shove (2010), "the challenges of climate change are such that many familiar ways of life and many of the patterns of consumption associated with them are fundamentally unsustainable" (p. 1273). There are positive feedbacks in the consumptive US electricity system. Increased consumption leads to increased GHG emissions which has been shown to influence climatic variability and extreme weather events (IPCC, 2014). To help reduce energy consumption and related GHG emissions, Fisher and Newell (2008) suggest that both policy and the diffusion of relevant knowledge through effective communication as to influence positive behavior is necessary. The current study seeks to expand beyond merely identifying energy related problems in an effort to understand the mechanisms by which EE can be diffused directly into households.

3.2.1 Energy efficiency programs and climate

Energy related decisions to curb consumption, ranging from federal energy policy to the type of light bulb in the home, are people-centric. To help slow energy consumption and the related GHG emissions in the US, governmental agencies as well as investor-owned, stateregulated utility companies engage in EE programs to influence adoption of technologies and pro-conservation behaviors (Craig & Allen, 2014). There are billions in incentive dollars available from utilities and governmental agencies for residences to become more efficient (Gillie et al., 2014), with over 30 million US dollars deployed in the focal state in 2012. The deployment of incentives to those who utilize these programs is largely based on a deemed savings model, in that efficiency upgrades are assigned a kilowatt-hour (kWh; unit of measurement of electricity) savings value approved by a state regulatory body (Craig & Allen, 2014). Relying on these assigned values instead of using pre- and post-test consumption analysis make it difficult to gauge the true impact of such programs. Because of these complications, the current study will focus on actual peak electricity kW savings reported by utility companies in lieu of deemed kWh household savings. Also, the study will focus only on indirect EE costs that include non-incentive spending such as marketing and administration, as direct costs are incentives paid based on the deemed kWh values.

Electricity consumption and electricity savings from EE programs were reported by utility companies with the EIA. However, there is no systematic control for climatic factors in these reports. In a longitudinal residential study, Jovanovic et al. (in press) demonstrated that temperature was the biggest determinant for increased electricity consumption, particularly during periods of extreme cold and hot temperatures related to electric heating and cooling equipment. Large empirical studies indeed demonstrated that both electricity (r = .84; Quayle &

Diaz, 1980) and natural gas (r ≥ .97; Timmer & Lamb, 2007) consumption are strongly linked to climatic factors such as heating degree days (HDD) and cooling degree days (CDD). HDD and CDD are measures of how much energy is needed to heat or cool a facility given local temperature conditions, where "A degree day indicates that the daily average outdoor temperature was one degree higher or lower than some comfortable baseline temperature" (EPA, 2014). According to Mourshed (2012), HDD and CDD are more reliable measures of climatic impact on energy consumption than temperature alone, thus they were included as the measures of climatic variability in this study.

Models predict increased temperature variability, including increased electricity demand associated with CDDs absent other factors (IPCC, 2014; McFarland et al., 2014; Yi-Ling et al., 2014). A salient factor not included in the models is efficiency (McFarland et al., 2014). The pricing for residential customers is traditionally volumetric, meaning that as demand increases for electricity, residential pricing stays the same (Schurr & Hauser, 2013). With the Southeast US projected to experience more weather extremes and climatic variability associated with increasing temperature (Feng et al., 2015; Ingram et al., 2013), the deployment of effective efficiency programs to offset the projected demand in electricity (McFarland et al., 2014) in the residential sector without the option of variable pricing is crucial. Efficiency programs can range from purchasing discounted efficient lighting at major retailers to making home retrofits (Craig & Allen, 2014), with the entire portfolio of electricity savings measures needed to combat increased demand (Sioshansi et al., 2013).

The current study examines the influence of EE programs (i.e., actual kW savings and costs of programs), HDD, and CDD on kWh consumption per consumer in Southeast US. More

specifically, the study examined these relationships primarily relative to electric heating applications and electric cooling applications:

Research Question 1: How much variability in residential kWh consumption used for heating and cooling is explained by climatic factors, EE program actual kW savings, and EE costs?

3.2.2 Communication and the residential electricity consumer

Communication with electricity consumers is essential to ensure that energy savings occur. For instance, Delmas et al. (2013) found in a meta-analysis that incentive programs administered without feedback mechanisms resulted in increased energy consumption in the home, the opposite of the desired effect. To combat results in the wrong direction, or the rebound effect (Gillingham et al., 2013), states are increasingly using feedback rich deep-savings approaches that behaviorally empower residential customers to reduce electricity consumption. Asensio and Delmas (2015) saw consumption reductions when this strategy was used with residential electricity customers. Darby (2006) demonstrated that rich feedback can behaviorally lead to energy savings between 5% and 15%, whereas behavioral reduction in consumption outside of feedback is minimal. Craig & Allen (2015) had similar results, in that households saw a year-over-year drop of over 10% in electricity consumption after a behavioral intervention that included rich feedback when controlling for climatic variability. While there are some in the US that are deploying aggressive behavioral programs (e.g., O'Power, the Shelton Group), proactive behavioral interventions in residences remain the exception. It is not as easy as just providing incentives or presenting a message related to participating in EE and expecting people to change, however. Awareness about efficiency and related programs remains low among adults and children (Craig & Allen, 2015; Craig & Allen, 2014). For instance, in a recent study, only

21% of residences interviewed recalled receiving information or educational materials about efficiency (Langevin et al., 2013).

Dewaters and Powers (2009) noted that energy literacy has an affective, or emotional, element. Mis-information and previously formed attitudes have the potential to deter the receipt of new information and further solidify potentially negative attitudes that can deter positive behaviors. In fact, Craig & Allen (2014) found individuals who did not know about utility EE programs were less supportive of the use of alternative energy, which has the potential to further hinder the development of non-carbon emitting infrastructure. Also, when considering EE and other pro-conservation actions, the gap between positive attitudes and perceptions and the actual behavior is well-documented (e.g., Allen, forthcoming; Gupta & Ogden, 2009; Pickett-Baker and Ozaki, 2008; Unsworth et al., 2013). This gap highlights the need to use effective communication and messaging to build knowledge and positive attitudes that increase the likelihood of pro-conservation behaviors.

The theory of planned behavior (TPB; Ajzen, 1991) states that people become aware of a topic, form attitudes and perceptions about the topic, and plan to behave accordingly. When dealing with conservation related behaviors, the TPB is complicated by low awareness levels about EE and the gap between perceptions and behavior. Engagement in socially responsible programs such as efficiency can influence individual attitudes and affect (Craig & Allen, 2013), increasing the likelihood of organizationally desired behaviors such as residential participation in efficiency programs. Micro-level engagement by residences can also increase the participation of others in socially responsible and / or environmental initiatives by providing normative pressures or nudges (Cialdini, 2003; Thaler & Sunstein, 2008). In organizational settings, normative social pressures in both theory and practice are related to pro-conservation behaviors such as energy

consumption (Lulfs & Hahn, 2014; Nilsson et al., 2015). Differences in environmental attitudes and behaviors have emerged in the past, however, on demographic factors including age, gender, political party affiliation, and income (e.g., Atkamis, 2011; Craig & Allen, 2014; Brouhle & Khanna, 2012; Coffey & Joseph, 2013).

Individuals are paying into efficiency programs in the form of riders or fees on their electric bills, but the majority of residential ratepayers remain unaware about programs and do not participate (Craig & Allen, 2014; Langevin et al., 2013). Of interest to utility organizations pursuing consumptive behavior changes, individuals not aware of environmental actions by an organization perceived actions less favorably than those who were aware (Craig & Allen, 2013). Consistent with these findings, Liu et al. (2015) found that residents who were involved prior to efficiency upgrades were more likely to realize higher energy savings once a retrofit occurred. In this study, residents were asked if they were aware of rebates for efficient lighting or if they had purchased rebated lighting as part of utility organization efficiency programs. Because of the historically low awareness and participation rates in residential efficiency programs, it was necessary to focus on the most wide-spread program to increase the likelihood that the resident had participated (Craig & Allen, 2014; Langevin et al., 2013). For investor-owned utility companies in particular, the consumer is a very important part of the organization, as consumptive energy patterns directly influence emissions related to production. Participation by residential energy consumers for utility companies is a cost-effective means to reduce consumption and emissions when faced with the increasing need for expensive energy infrastructure as well as regulations to aggressively reduce emission such as the Clean Power Plan recently proposed by the EPA (2014). If utility organizations are able to increase awareness and participation in entry-level programs, such as rebates for efficient lighting that are provide

more electricity savings per dollar spent than more robust measures (Molina, 2014), and provide feedback to the residential end-user, the likelihood of successful program deployment and savings persistence increases (Asensio & Delmas, 2015; Craig & Allen, 2014; Craig & Allen, 2015; Liu et al., 2015).

With a better understanding of the interaction of energy consumption with the climate and EE programs in the focal state, the current study also seeks to understand what differences among residential electricity consumers are driving participation in efficiency programs, influencing residential consumer perceptions about utility companies, and influencing residential consumer support for efficiency programs and clean energy. The current study examines the differences among residential energy consumers in terms of perceived utility motives for efficiency programs, support for government subsidies for EE, and support for utility company use of clean energy controlling for awareness levels, past participation in utility programs, and demographic factors. The basic framework of the TPB is utilized, exploring how residential awareness and participation in programs can influence attitudes and perceptions, which in turn can influence residential electricity consumer support for clean energy and government EE subsidies. The following research questions are proposed:

Research Question 2a: Is there a difference between residential electricity consumers participation in EE programs based on residential electricity consumer awareness levels?

Research Question 2b: Is there a difference in perceptions about utility motives for providing efficiency programs, support for government policy for efficiency programs, and support for utility use of clean energy based on residential electricity consumer awareness levels, participation in utility programs, and demographic factors?

3.3 Materials and methods

3.3.1 Procedure

HDD and CDD climatic data were obtained for the focal state from 1992 through 2012 using NCAR command language version 6.3.0 (2015). HDD and CDD were annualized to examine climatic trends related to temperature variability from 1992 until 2012. Energy consumption and efficiency savings were calculated from data retrieved for the years 1992 through 2012 from Form EIA 861 and the EIA website (http://www.eia.gov/electricity/data/eia861/). Energy consumption was calculated as kWh per consumer. Efficiency savings were calculated as the actual peak kW savings per consumer in terms of incremental savings (i.e., within year kW savings from new EE participants) and annual savings (i.e., the lifetime kW savings from all EE participants in current and past years). EE costs were calculated as indirect cost per consumer, and included costs not directly related to implementing EE programs such as marketing, measurement and evaluation, and administration.

Using a stratified random sampling technique (Trochim, 2001), a phone survey was administered in June 2012 to residential electricity consumers in a single Southeastern US state in four counties among registered voters. Phone numbers included both wired and cell phones, depending on the number used for voter registration. Rural/urban, income, party, and race were the socio-economic factors used for county selection. A phone survey was used for two reasons. First, while over 87% of the US population is connected to the internet today (http://www.internetworldstats.com), many more rural states, such as the focal state, have over 30% of their residents who do not use the internet according to the 2009 US Census. Second, Xing and Handy (2011) noted that while there was a difference between internet and phone results on demographic questions, there was no significant difference for attitudinal and

behavioral questions. The commercial polling firm provided pre-verified demographic data, making the phone survey suitable for the research.

According to the PewResearch Center for the People & the Press (2012), typical response rates for phone surveys are 9%. The current study had a response rate of 10.7% (n = 2,450), and it took each respondent approximately 10 minutes to answer 12 questions (age, party, and income were pre-verified and provided). The commercial polling firm completed the 2,450 surveys from a pre-selected group of 500,000 potential residential electricity consumer respondents. The large sample size increased the internal validity and decreased the margin of error (Trochim, 2001). The number of respondents using the stratified random sampling method returned better than a 5% confidence interval at the 95% confidence level for the sample (http://www.surveysystem.comfsscalc.htm).

3.3.2 Sample

Concerning gender, 35% of the respondents were male (n = 416) and 65% of the respondents were female (n = 774). In terms of race, respondents were 74.1% (n = 859) White, 19.3% (n = 224) Black, .6% (n = 7) Hispanic, and 6% Other. 76.3% of the respondents were Democrat, and 23.7% were Republican. 19.1% (n = 468) of the respondents were in the lowest income bracket from 0 – 19 thousand dollars, and the second largest income bracket (100 – 124 thousand) included 11.3% of respondents (n = 277). Ages ranged from 20 to 99 and was older (Mean = 67.5, SD = 15.9, n = 2,450). 24.4% (n = 599) of the respondents were aware of utility efficiency programs, 41.1% (n = 1,008) were unaware of the programs, and 34.4% (n = 843) were mis-informed about the programs (i.e., answer that programs did not exists when in fact programs were available). 20.6% (n = 426) had participated in utility efficiency programs, 63.5% had not (n = 1,311), and 15.8% (n = 327) were unsure. According to the United States Census

Bureau (2015), race percentages were approximately the same for the focal state as the sample, average income per household in the focal state fell within the average income bracket for the sample (50k - 59k), and there were approximately 15% more women respondents for the sample.

3.3.3 Measures

A full list of energy consumption, EE savings, climate, and EE costs variables are provided in Table 1.

Single-item Likert type questions traditionally utilized in political polling have recently been successfully deployed in academics and industry alike to examine environmental related topics (Craig & Allen, 2014; Coffey & Joseph, 2013; Shelton Group, 2011). The proposed survey consisted of 12 Likert-type questions. Because the commercial polling company has previously validated data for age, party affiliation, and income, it was not necessary to include these items in the phone survey. Compact florescent light (CFL) bulbs are recognizable to consumers due in part to wide-scale availability and point-of-sale placement efforts by retailers and manufacturers in the US. The focal utility efficiency program included on the survey instrument was discounted CFLs because of the entry-level nature of CFLs, the relative affordability compared to more capital intensive efficiency upgrades such as an energy audit, and the increased likelihood that residential electricity consumers may have recently purchased CFLs.

The question that gauged awareness had three response categories including (1) yes (2) no (3) don't know: "Does your electric utility provider offer discounts or coupons that you can use to buy energy efficient compact florescent light bulbs?" The question that gauged participation had three response categories including (1) yes (2) no (3) unsure: "Have you used

discounts or coupons from your electric utility provider when purchasing energy efficient compact florescent light bulbs?"

Two questions gauged residential electricity consumer perceptions about utility company motives for offering energy efficiency programs, both with Likert-type response categories from (1) strongly agree to (5) strongly disagree: "My electric utility provider offers discounts or coupons to purchases energy efficient compact florescent light bulbs because they don't want me to waste money on my bill," and "My electric utility provider offers discounts or coupons to purchase energy efficient compact florescent light bulbs because they want to help me save money on my bill."

Two questions were asked to gauge residential electricity consumer perceptions about support for government subsidies and utility use of clean energy sources, both with Likert-type response categories from (1) strongly agree to (5) strongly disagree: "I believe that it is okay for the state or federal government to subsidize the cost of energy efficiency programs that utility companies provide," and "I believe that utility companies should use more clean or alternative forms of energy."

3.3.4 Statistical analysis

To prepare the electricity data for analysis, national residential energy usage survey figures (EIA, 2009a, 2009b) were used to allocate kWh consumption for electric heating and cooling applications. In the focal state, 15.71% of the electricity consumed was for electric heating and 15.62% for cooling, with 68.67% for all other household electricity uses. In the focal state, 62.86% of households used electricity as a heating fuel source. To calculate the total percentage of electricity consumed for heating applications, this value was multiplied by the percentage of residential energy used for heating (i.e., 25.00%). The same procedure was used

for cooling, where 98% of residents used electricity as the fuel source for air conditioning, and 16.00% of the total energy consumed yearly in the state was for air conditioning. To determine the kWh allocations for heating and cooling, the following formulas were used:

62.86% households used electricity as a heating fuel source X 25.00% overall energy was used for heating = 15.71% of overall electricity consumed was for heating

98.00% households used electricity as an air conditioning fuel source X 16.00% overall energy was used for cooling = 15.62% of overall electricity consumed was for cooling According to the National Appliance Energy Act of 1987 (1987) non-electric furnaces must at minimum meet a 78% efficiency standard in the US. However, older equipment still in use is between 56% and 72% efficient (US Department of Energy, 2014). Consistent with industry practice, a conservative 80% efficiency rating was applied to non-electric heating applications. A 100% efficiency assumption consistent with industry practice was utilized for electric heating and all cooling applications. The 62.86% value for electric heating equipment was discounted from an original value of 69% electric heating equipment used in the focal state to account for the additional 6.14% of total heating energy loss due the 20% inefficiency.

The climatic and energy data were graphically examined to identify trends. The data were detrended using a differencing approach ($w_t = x_t - x_{t-1}$), where x is the original value at time $_t$ and w is the first degree differencing value at time $_t$ (Anderson, 1976; Yaffee & McGee, 2000). Several steps of differencing can be calculated to detrend the data. Anderson (1976) noted that if the variance of an additional step of differencing increases, the sample has been over-differenced. For each variable, differencing for successive degrees was conducted until an increase in variance was observed, where the additional step was not included. The observation of standard deviations for the sample for each successive step of differencing ensured that the

data was detrended to the proper degree and not over-differenced. Table 1 presents the original values of electricity consumption, climatic, efficiency electricity savings, and costs variables as well as each successive degree a decrease in variance occurred compared to the preceding value. The study used residential survey usage data (EIA, 2009b). The overall kWh electricity consumption per consumer was multiplied by the percentage of electricity allocated above for heating (i.e., 15.71%) and cooling (i.e., 15.62%).

IBM SPSS Statistics version 22 was used for statistical analysis. Descriptive statistics were calculated for the electricity consumption, climatic, EE savings, and EE costs variables (see Table 1). Regression models were run using stepwise linear regression. The first model examined the variability in heating kWh consumption per consumer explained by HDD, incremental (within year) and annual (accumulated) kW savings per consumer, and indirect EE costs per consumer. The second model examined the variability in cooling kWh consumption per consumer explained by CDD, incremental and annual kW savings per consumer, and indirect EE costs per consumer. HDD, CDD, and incremental kW savings per consumer used original values as the detrending increased variance after the first step. kWh per consumer for heating and cooling applications, annual kW savings per consumer, and indirect EE costs per consumer each used detrended values as decrease in variance was observed.

One-way ANOVAs were utilized to examine the difference in residential energy consumer participation in EE programs based on their awareness of the programs. Likewise, One-way ANOVAs were utilized to examine the differences in sorting variables in terms of perceived utility company motives for EE programs, support for government subsidies for EE programs, and support for utility use of clean energy. Sorting variables included residential

electricity consumer awareness about EE programs, previous participation in EE programs, and the demographic factors of gender, race, political party, and income.

3.4 Results

3.4.1 Energy consumption, climate, and energy efficiency

Stepwise linear regression was utilized to examine Research Question 1, which sought to explain variability in kWh consumption for heating and cooling applications. Indirect EE costs, or those costs not directly related to utility incentive funds, was the only significant predictor for kWh per consumer for heating applications, with the one-step model accounting for 16.8% (Adjusted $R^2 = .168$) of the variability (Standardized $\beta = -.458$, p < .001; F = 5.03, p < .05). A two-step model emerged for kWh per consumer for cooling application where indirect EE costs (Standardized $\beta = -.507$, p < .05) and CDD (Standardized $\beta = .442$, p < .05) explained 33.6% (Adjusted $R^2 = .336$; F = 6.06, p < .01) of the variability (see Table 2 for full results).

3.4.2 Residential energy consumer differences

One-way Anovas and Scheffe's post-hoc tests were utilized for all portions of Research Question 2. Scheffe's post-hoc tests demonstrate differences among individual groups. Research Question 2a asked if participation was significantly different for those who are aware, misinformed, and unaware about utility efficiency programs. A significant difference was observed (F = 309.92, p < .0001), with those aware significantly more likely to participate in EE programs than mis-informed or unaware consumers, and mis-informed consumers significantly more likely to participate than unaware consumers. Research Question 2b asked if there was a significant difference in perceptions about utility motives for providing efficiency programs, support for government policy for efficiency programs, and support for utility use of clean energy based on residential electricity consumer awareness levels (see Table 3). As shown in Table 3, for each

variable of interests there was a significant difference in perceptions and support based on consumer awareness at the p < .05 level. Research Question 2b also asked if there was a significant difference in perceptions about utility motives for providing efficiency programs, support for government policy for efficiency programs, and support for utility use of clean energy based on residential electricity consumer participation (see Table 4). There were significant differences for each relationship, with those who participated differing from those who had not participated and those who were unsure if they had participated.

Research Question 2b asked if there were significant differences in perceptions about utility motives for providing efficiency programs, support for government policy for efficiency programs, and support for utility use of clean energy based on residential electricity consumer demographic factors including gender, race, political party, and income as well (see Table 5). There were significant differences between males and females on utility motives for not wanting consumers to waste money (F = 10.41, p < .001), utility motives for wanting to save consumers money (F = 16.73, p < .0001), consumer support for subsidies (F = 46.56, p < .0001), and consumer support for utility use of clean energy (F = 32.654, p < .0001). In each instance, females were more likely to perceive the utility favorably, support subsidies, and support clean energy. Likewise, significant differences were found for each of the four items of interest with regards to race (see Table 6). There were significant differences between Democrats and Republicans on utility motives for not wanting consumers to waste money (F = 11.05, p < .0001), utility motives for wanting to save consumers money (F = 8.05, p < .0001), consumer support for subsidies (F = 31.62, p < .0001), and consumer support for utility use of clean energy (F = 37.62, p < .0001). In each instance, Democrats were more likely to perceive the utility favorably, support subsidies, and support clean energy. There were significant differences among income groups on utility motives for not wanting consumers to waste money (F = 3.18, p < .0001), utility motives for wanting to save consumers money (F = 2.28, p < .01), consumer support for subsidies (F = 4.41, p < .0001), and consumer support for utility use of clean energy (F = 2.10, p < .05). Please see Figure 6 for the breakdown of income range responses to each of the four items.

3.5 Discussion

Results from Research Question 1 highlight the impact of the climatic variability experienced in the focal state, and the role that energy efficiency has on reducing residential electricity consumption. There are over \$6 billion spent by utilities on each year to reduce electricity consumption (Gilleo et al., 2014), and in the Southeast US electricity is the primary fuel source for both heating and cooling (EIA, 2009b). Moreover, states in the focal region use proportionally more fossil fuels such as coal to produce electricity (EIA, 2015), intensifying greenhouse gas emissions related to electricity consumption. In order to reduce the climatic impact of residential electricity consumption in this region related to heating and cooling, it is crucial to understand the unique interactions between efficiency efforts and changing climatic characteristics.

Regarding kWh consumption per consumer allocated to heating, indirect costs per consumer, including expenses such as marketing and administrative for running EE programs, was the only significant predictor. The negative relationship suggests that as spending on programs not allocated directly to incentives increases, kWh consumption per consumer for heating applications in fact decreases. Globally, mean temperatures are rising (IPCC, 2014). Consistent with this trend in the focal state there was a slight downward trend in HDD, an indication that there are less cold days requiring heating applications. However, kWh

consumption for heating was not significantly related to HDD. CDDs were trending up during the study period in the focal state. CDD exhibited a positive relationship that resulted in an overall two-step model that also included indirect EE costs and explained 33.6% of the variation in kWh consumption for cooling. Consistent with previous research (Bradshaw et al., 2013; Craig & Allen, 2015; Jovanovic et al., in press), our results support the notion that climate is playing a significant and important role in energy consumption and savings.

Previous research suggests that communication and inclusion in efficiency efforts are crucial in reducing consumption (Craig & Allen, 2015; Darby, 2006; Delmas et al., 2013; Liu et al., 2015). There has been a rapid expansion of EE spending and communication in recent years (Gilleo et al., 2014). However, in the focal state a significant decrease in actual electricity savings from efficiency efforts for heating and cooling applications was not present. Indirect costs are associated with activities such as marketing and outreach. While efforts associated with EE spending could very well be influencing actual kWh consumption related to heating and cooling behaviors, it is feasible that the data reported by utility companies may not be robust enough to clearly capture these savings.

Consistent with the progression of the TPB, findings from Research Question 2a confirmed that residential electricity consumers who were aware of efficiency programs were significantly more likely to participate than those who were either unaware or who were misinformed. A post-hoc test indicated that those who were mis-informed (that is, stated there were no efficiency programs when in fact there were) were significantly more likely to participate than those who are completely unaware. When asked about participation in terms of using a rebate or discount to purchase an energy efficient CFL, the individuals who responded that there were no EE programs in fact had used significantly more rebates or discounts than those who were

completely unaware. This finding demonstrates a potential shortcoming with the effectiveness of utility company communication efforts to increase participation, reduce consumption, and reduce emissions. Without rich feedback and communication related to efficiency measures (Craig & Allen, 2014; Darby, 2006; Delmas et al., 2013), the trajectory of increased energy consumption will likely continue, and the additional benefits of diffusion of socially conscious activities will remain unrealized (Cialdini, 2003; Thaler & Sunstein, 2008). Further, the TPB states that awareness and knowledge help to build positive attitudes and perceptions towards a topic. Participation without awareness bi-passes this step, decreasing the potential for positive attitudes, perceptions, and future behaviors to occur (Ajzen, 1991).

Research Question 2b asked if there was a significant difference in perceptions about utility motives for providing efficiency programs, support for government policy for efficiency programs, and support for utility use of clean energy based on residential electricity consumer awareness levels, participation in utility programs, and demographic factors. Those who were aware of utility EE programs were significantly more likely to perceive that utilities offered programs as to help the residential consumer not waste money. With regards to the utility company's motives being to save the consumer money, those who were aware were significantly more likely to favorably view utility motives than the unaware or mis-informed individual, and the unaware individual was significantly more likely than the mis-informed individual to view motives favorably. When considering the relationship between awareness and participation addressed with Research Question 2a, these findings are not favorable for utility companies. While the mis-informed consumer is not as likely as the informed to participate, they are more likely than the uniformed to participate, and they are the most likely group to negatively view

utility motives for EE programs. In keeping with the TPB, mis-information is more strongly related to negative attitudes than no information at all.

Consistent with Pelletier and Sharp (2008), positive attitudes and perceptions appeared to follow knowledge and literacy associated with awareness about efficiency programs. Kim (2011) states it takes more than awareness for the enactment of pro-environmental actions such as support for policy or utility company use of clean energy. With the TPB awareness is the starting point to build positive attitudes and perceptions, and to move towards action. The findings of the study support previous research (e.g., Craig & Allen, 2014; Langevin et al., 2013) that awareness remains low, making it less likely on the aggregate the pro-conservation attitudes or behaviors will occur.

A slightly different picture emerged with regards to government subsidies for EE and utility use of clean energy. Aware consumers were only significantly more likely than unaware consumers to be more supportive of subsidies for EE, and both the aware and mis-informed consumers were significantly more likely than the unaware consumers to support utility use of clean or alternative energy. Considering that mis-informed consumers trust utility motives less than the other groups, it is not surprising that they are not supportive of subsidies for utility companies, even if they are more likely than the unaware to participate in efficiency programs. However, the mis-informed consumer is more similar to the aware consumer with support for utility use of clean energy. The reasoning behind this support may vary, however. It stands to reason since mis-informed consumers are more likely to view utility companies less favorably than other groups, that the support for the use of clean energy could be related to holding the utility company accountable. For Research Question 2c, those who participated in utility EE programs were significantly different from both the unaware and the mis-informed for all

independent variables of interest. Keeping in mind those who were aware of efficiency programs were more likely than the mis-informed or unaware, these findings are consistent when viewed through the lens of the TPB.

Consistent with past research (e.g., Brouhle & Khanna, 2012; Langevin et al, 2013; Liu & Shen, 2011; Manley et al., 2013; Peterson & Liu, 2008), significant differences based on demographic factors emerged. The differences between women and men and Democrats and Republicans were the most pronounced, with women and Democrats perceiving the utility company more favorably on both items and being more supportive of both subsidies and utility use of clean energy. This supports previous literature that shows women and Democrats are more supportive pro-environmental initiatives than men (e.g., Atkamis, 2011; Craig & Allen, 2014; Coffey & Joseph, 2013).Regarding race, consumers who self-identified as Black and Other were significantly more supportive of both subsidies for utility efficiency programs and utility use of clean energy than consumers who self-identified as White.

As shown in Figure 6, there were significant differences based on income as well for both utility motive independent variables and support of government subsidies. Post-hoc tests indicated that there were only two groups that were significantly different from one another, residents in the 0-19K income bracket and residents in the 100-124K income bracket. Residents in the lowest income bracket (0-19K) perceived utility motives more favorably than the 100-124K income bracket, and were more supportive of government subsidies. Specific to subsidies for utility bill assistance, the federal government established the need-based Low Income Housing Assistance program (LIHEAP) in 1981 to help with heating and cooling expenses to avoid service disconnect, to respond to extreme weather events that interrupt service, to help with low-cost home upgrade projects to lower demand, and to provide consulting services

to help reduce consumption (Perl, 2013). According to Perl \$3.615 billion were appropriated to fund LIHEAP in 2014, and in 2009 an estimated 35 million low-income households were eligible to participate. It may be that higher awareness levels and participation in government assistance or subsidy programs such as LIHEAP are similar to awareness and participation to EE programs in the current study, leading to higher levels of support for policy. One of the most interesting findings was with the highest income bracket (250K +). While not the most supportive income bracket, this group was more consistent with the lower income brackets than the higher income brackets, indicating that while the extremely wealthy may not perceive utility motives more favorably, they are in fact more supportive of energy and emissions reduction through efficiency subsidies and clean energy infrastructure.

3.5.1 Conclusions

The results of the current study demonstrate that climatic variability can play a major role in kWh consumption among residential electricity consumers, particularly in areas that are reliant on electricity for heating and cooling homes. Bradshaw et al. (2013) note the interactive nature of climatic conditions with regards to efficiency. Fisher and Newell (2008) discuss the need for both policy (e.g., utility EE programs, electricity pricing, energy mix) as well as the diffusion of knowledge to deploy environmental technologies and processes. In the focal state, policy continues to expand the spending on utility EE spending (Gilleo et al., 2014). However, the lack of actual, verifiable electricity savings related to heating and cooling suggests that communication, as well as the diffusion of technologies and processes related to proconservationism, can be improved when targeting residential consumers.

The current study sought to lay out a clear path using the TPB that can move residential electricity consumers from awareness about utility programs to participation in programs.

Furthermore, the study sought to draw the connection between awareness, perceptions about utility motives, and consumer support for government subsidies and utility clean energy use.

While not causally related, the study did show that those who were aware of EE programs had more favorable perceptions about utility motives, were more likely to participate in programs, and were more likely to support subsidies and clean energy use by utilities. The research offered an oft-utilized approach that examined the interaction between the climate, the environment in terms of energy consumption, and residential electricity consumers. The findings in the focal Southeast US state are very telling, providing support that climate is the driving influencer of kWh consumption related to cooling and that indirect EE spending is influencing kWh consumption related to both heating and cooling. Finally, people who are aware of efficiency programs are more likely to participate, perceive utility motives more favorably, and maybe most importantly, support consumption reduction and emissions reductions steps by governmental entities and utility companies to help combat the anthropogenic induced climatic variability and change (IPCC, 2014).

3.5.2 Practical implications

The current study demonstrated the need for effective communication between organizations and those at the micro-level when deploying efficiency programs to help mitigate climatic and resource availability issues. There are billions of dollars (Gilleo et al., 2014) being deployed for EE programs, however, actual, verifiable electricity savings were not significantly related to the residential kWh consumption associated with heating or cooling. Delmas et al. (2013) and Darby (2006) noted that the energy savings are closely related to feedback and communication. Those who are aware are more likely to participate and have positive views about the utility company's motives, which in turn could help to expand socially conscious

behaviors to other consumers through normative pressures or nudges (Cialdini, 2003; Thaler & Sunstein, 2008). However, despite residential consumers paying into the EE programs on every month's utility bill, the vast majority are not aware or are mis-informed, and have not participated. This raises a serious question about the motives of the utility companies for the programs, and the manner in which spending is occurring as to engage residential consumers in true and transformational change to become more efficient. Also, by utilizing a method that explicitly takes into account climatic variability and EE programs, on a macro-scale this information could be used to more accurately forecast the supply and demand of energy to help answer difficult energy security and policy issues.

3.5.3 Limitations and future research

The current study is not without limitation. First, reporting for energy consumption, EE savings, and costs was annualized. Steps were taken to utilize previously collected residential survey information about consumptive habits in order to combat this shortcoming. Next, there were a limited number of years of efficiency kW and kWh consumption data that could be matched with the HDD and CDD data. In many states, however, spending has been limited until recently with regards to efficiency programs, so data available to analyze is limited. Also, the energy data was aggregated at the state-level due to utility company reporting practices. With the availability of 4 kilometer resolution climatic data back to 1981, the relationships between climate, consumption, and efficiency could be much better understood with location data for residences which is currently unavailable on a macro scale.

The humanistic-focused portion of the study was exploratory in nature, seeking to more clearly understand differences in ratepayer awareness, perceptions, and behaviors. The large sample size (n = 2,450) helped to overcome validity issues related to study limitations that

included: the use of cross-sectional data, the lack of pre- and post-test design, the use of a phone survey, the higher ratio of Democrat respondents, the higher ratio of female respondents, the older age of the sample, and the use of nominal level data for awareness and participation items.

States in regions outside the Southeast US are not as reliant on electricity for heating and cooling (EIA, 2009b), and are also unique in efficiency policies and deployment down to the state-level (Gilleo et al., 2014). Future research could expand to the effectiveness of efficiency programs at the state-level when controlling for climatic variability for all of the lower 48 states. Also, climate modeling could be utilized to predict trends in HDD and CDD to more accurately predict electricity consumption on a state-by-state basis when accounting for the effectiveness of current efficiency programs and spending. From a regulatory stand-point, future research could be conducted to examine the effectiveness of "deemed" savings versus actually reported savings. The current study demonstrates significant differences in pro-environmental attitudes, support for EE subsidies, and support for clean energy. Future research should be expanded nationally in the US to determine the driving factors for residential EE support and clean energy use by utility companies among residential electricity consumers both within similar climate regions and on a state-by-state basis. Researchers have a unique opportunity to move forward by integrating change agents (e.g., residential electricity consumers) into climate and energy studies as to increase the likelihood of the enactment of positive change to mitigate pressing issues such as anthropogenic forced climate change and resource availability.

3.6 References

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3.7 Figures

Table 1. Descriptives for electricity, climate, and costs variables.

Variable	N	Min	Max	Mean	SD
Total kWh ₀	21	10,266.00	14,538.00	12,581.38	1,070.32
Heating kWh 0	21	1606.97	2284.50	1977.07	168.19
Heating kWh 1	21	-110.03	254.79	24.09	95.57
Cooling kWh 0	21	1597.23	2270.65	1965.08	167.17
Cooling kWh 1	21	-109.36	253.24	23.93	94.99
CDD_0	21	789.59	1,302.44	1,042.16	134.76
HDD _0	21	1515.21	2137.62	1,854.66	153.87
EE IA kWh 0	21	.00	65.60	6.93	13.70
EE AA kWh ₀	21	.00	3.80	.6810	1.12
EE AA kWh 1	21	-2.89	.44	16	.68
Indirect costs 0	21	.00	9.45	1.10	2.42
Indirect costs 1	21	.00	4.53	.45	1.07
Indirect costs 2	21	82	3.65	.22	.87

Note. The differencing (Anderson, 1976) detrending method and the equation from Yeffee and McGee (2000) were utilized. Subscript values are as follows: 0 = no differencing, actual values; 1 = first degree of differencing; 2 = second degree of differencing.

kWh figures are for overall total kWh consumption per consumer, kWh consumption allocated to heating per consumer, kWh consumption allocated to cooling per consumer, and kWh consumption allocated to all other electric applications per consumer. Heating degree day (HDD) and cooling degree day (CDD) experienced a slight increase in variation, so the original values were used. EE IA kWh refers to actual energy efficiency program kWh savings per consumer for incremental (with-in year) reporting, and EE AA kWh refers to actual energy efficiency program kWh savings per consumer for annual (lifetime) reporting. Indirect costs are periphery costs such as administrative or marketing per consumer, and do not include direct and / or incentive costs of programs.

Table 2. Stepwise linear regression models for kWh per consumer for heating application and kWh per consumer for cooling application.

Step and variables	β	SE	В	t	p	
Heating kWh						
Step 1 ($AdjR^2 = .168$)						
Indirect costs 2	458	22.36	-50.157	-2.24	.037*	
Cooling kWh						
Step 1 $(AdjR^2 = .168)$						
Indirect costs 2	458	22.23	-49.85	-2.24	.037*	
Step 2 $(AdjR^2 = .336)$	ating kWh 10 1 ($AdjR^2 = .168$) 21 irect costs 2458 22.36 -50.157 -2.24 .037* 22 irect costs 2458 22.23 -49.85 -2.24 .037* 23 irect costs 2458 22.23 -49.85 -2.24 .037* 24 2 ($AdjR^2 = .336$) 25 irect costs 2507 19.977 -55.26 -2.77 .013*					
Indirect costs 2	507	19.977	-55.26	-2.77	.013*	
CDD ₀	.442	.129	.312	2.41	.027*	

Note. Indirect costs were detrended to the 2^{nd} degree. * = p < .05.

Table 3. Relationship between awareness and residential electricity consumer perceived utility company motives, support for government subsidies for EE, and support for utility use of clean energy.

Variable	Aware	Mis-Informed	Unaware	F	p
Utility Company Not Waste	2.06a	2.81b	2.90b	75.35	.000****
	(1.12)	(1.27)	(1.03)		
Utility Company Save	2.17a	3.09c	2.87b	77.18	.000****
	(1.14)	(1.28)	(1.08)		
Govt. Subsidy Support	3.24a	3.14	3.29b	3.67	.026*
	(1.33)	(1.48)	(1.42)		
Utility Clean Energy Support	2.76a	2.52a	2.19b	10.34	.000****
	(1.68)	(1.67)	(1.57)		

Note. * = p < .05, ** = p < .01, *** = p < .001, **** = p < .0001. Standard deviations appear in parentheses below means. Means with differing subscripts within rows are significantly different at the p < .05 based on Scheffe post-hoc paired comparisons.

Table 4. Relationship between participation in EE programs and residential electricity consumer perceived utility company motives, support for government subsidies for EE, and support for utility use of clean energy.

Variable	Participant	Non-Participant	Unsure	F	p
Utility Company Not Waste	2.03a	2.83b	2.72b	62.67	.000****
	(1.11)	(1.18)	(1.12)		
Utility Company Save	2.03a	2.97b	2.82b	77.16	.000****
	(1.11)	(1.22)	(1.01)		
Govt. Subsidy Support	2.39a	2.84b	2.84b	11.76	.000****
	(1.34)	(1.39)	(1.36)		
Utility Clean Energy Support	t 1.91a	2.16b	2.37b	8.07	.000****
	(1.15)	(1.21)	(1.30)		

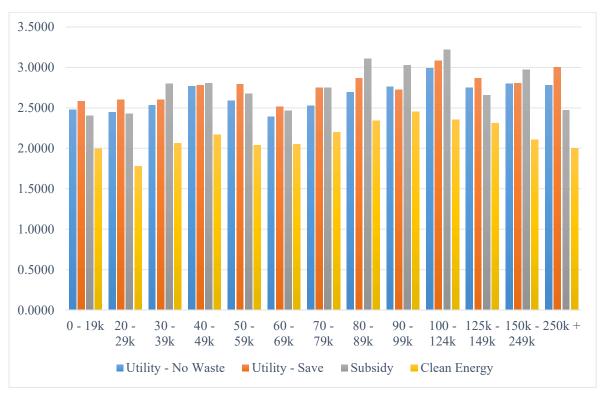
Note. * = p < .05, ** = p < .01, *** = p < .001, **** = p < .0001. Standard deviations appear in parentheses below means. Means with differing subscripts within rows are significantly different at the p < .05 based on Scheffe post-hoc paired comparisons.

Table 5. Relationship between race and residential electricity consumer perceived utility company motives, support for government subsidies for EE, and support for utility use of clean energy.

Variable	W	В	Н	O	F	p
William Co. N. W.	2.71	2.40	2.20	2.001	4.46	0.0 4 vlovin
Utility Company Not Waste	2.71(1.19)	2.48a (1.16)	(1.25)	2.99b (1.28)	4.46	.004**
Utility Company Save	2.77a	2.56a	3.57	3.30b	7.53	.000****
	` ′	(1.21)	` ′	(1.09)		
Govt. Subsidy Support		2.15a (1.19)	3.71b (1.50)	3.03b (1.54)	18.72	.000****
Utility Clean Energy Support	2.17b	1.86a	` ′	2.35a	4.98	.002**
	(1.22)	(1.05)	(1.40)	(1.40)		

Note. * = p < .05, ** = p < .01, *** = p < .001, **** = p < .0001. W = White, B = Black, H = Hispanic, O = Other. Standard deviations appear in parentheses below means. Means with differing subscripts within rows are significantly different at the p < .05 based on Scheffe post-hoc paired comparisons.

Table 6. Relationship between income bracket and residential electricity consumer perceived utility company motives, support for government subsidies for EE, and support for utility use of clean energy.



Chapter 4: Craig, C. A., Allen, M. W. (2015). The impact of curriculum-based learning on environmental literacy, energy consumption, and policy. Utilities Policy 35, 41 – 49 (published).

4.1 Abstract

Policy related to energy efficiency programs implemented by utility companies should be informed by an understanding of building occupant behavior change. This case study utilized a longitudinal design and mixed methodology to assess the effect of curriculum-based experiential learning on elementary school students' environmental literacy and energy-saving behaviors. We found that the students significantly improved their environmental literacy. Normalizing kWh consumption for weather, we observed a decrease in energy consumption of more than 15% in student homes and more than 30% at the focal school.

Chapter 4: The impact of curriculum-based learning on environmental literacy and energy consumption with implications for policy

4.2 Introduction

There are serious utility policy implications for how taxpayer and ratepayer dollars are allocated to support energy-efficiency and clean-energy projects. Programs have focused on providing funds to offset the expense of cost-effective upgrades (Foster et al., 2012). With improved tracking mechanisms, more funding is being directed toward behavioral programs within utility efficiency portfolios (Gilleo et al., 2014). The potential exists to increase energy savings by engaging building occupants around efficiency upgrades. The current study focuses primarily on the potential effectiveness of environmental literacy-driven behavior change initiatives in schools, how these initiatives can result in decreased energy consumption at school and in student homes, and the need for policy-makers to consider the energy savings and student learning implications of such initiatives when allocating taxpayer and ratepayer dollars toward these programs. Studies that investigate energy use related to environmental literacy and behavioral change efforts are critically important as public K-12 schools and community residents face financial challenges related to rising energy prices and, in some areas of the U.S., variable supply.

Public schools face a growing need to become more energy efficient due to budgetary constraints and projected energy-cost increases. According to the National Center for Educational Statistics (NCES), budgetary constraints in elementary schools were a contributing factor to an increase in closures from 487 in 1995 to 1,073 in 2011 (United States Department of Education, 2013b). The NCES also reports that facility-related operating costs are second only to instruction-related costs in public schools (with instructional costs over six-times larger than

operational costs). As of the 2013-2014 school year, at least 35 states received less funding per student than prior to the 2008 recession (Leachman & Mai, 2014). Due in part to inefficiencies associated with aging infrastructures, it is estimated that schools have the potential to reduce energy consumption by 20% to 30% and save approximately \$2 billion through available energy efficiency measures and efficient behaviors (Schelly et al., 2012; United States Environmental Protection Agency (EPA), 2011).

Investor-owned and other energy utilities, as well as federal, state, and local governmental entities, provide incentives to help businesses, schools, and residents obtain energy savings (Craig & Allen, 2014). For instance, the California Clean Energy Jobs Act (Proposition 39) appropriated more than \$400 million to help local schools and community colleges implement energy efficiency and clean-energy projects (California Energy Commission, 2013). Based on an analysis of annual utility documents filed with the focal state, the funding allocation to schools is nominal compared to allocations for businesses and residents. Furthermore, school projects can be complicated by the need for school board approval for large capital outlays.

Some state governments have enacted policies related to behavioral change programs; however, funding in this area is minimal compared to the more than \$7 billion yearly offered by investor-owned utilities (IOUs) to upgrade facilities (Gilleo et al., 2014). Energy utilities have programs that provide incentives for investing in energy efficiency technologies. Funded efficiency efforts are policy driven and implemented by regulated utility companies (Craig & Allen, 2014). Most programs, however, tend to overlook the potential of behavioral change initiatives that focus on how building occupants (i.e., students and teachers) can positively impact energy savings. For example, as of 2011, only 10% of utility bills included messages designed to promote energy savings (Foster & Altshuler, 2011; Mazur-Stommen & Farley,

2013). This study recommends consideration of holistic behavioral-based programs, such as experiential learning and curriculum deployment, as a means of improving the effectiveness of energy-efficiency programs in schools and student homes.

Research has demonstrated that students can influence adults and help schools drive energy savings (e.g., Cross et al., 2010), with efficiencies achieved often greater than those associated with utility-directed efficiency programs. Students can be social change agents, and can normatively influence or "nudge" adults and their peers to participate in socially conscious activities such as energy conservation (Cialdini, 2003; Thaler & Sunstein, 2008). Although there are notable exceptions (e.g., Alliance to Save Energy's Green Schools program, a national environmental initiative among 5,000 K-12 schools) (Bulman & Ehrendreich, 2010), many school programs do little to promote environmental literacy and behavioral changes in students. For example, a review of first-round Proposition 39 Request for Proposals (RFPs) from California schools found that opportunities for learning and behavior change of school occupants (i.e., students, teachers, and administrators) were largely overlooked in favor of equipment and facilities. In general, efficiency programs do little to target occupant awareness, learning, or proenvironmental behaviors (Craig & Allen, 2014; Foster et al., 2012).

In a longitudinal study, Alcott and Rogers (2014) demonstrated that the cost-effectiveness of some behavioral programs has been understated because of overly conservative assumptions about energy savings. Darby (2006) found that direct feedback, such as that provided by smart meters, produced savings of between 5% and 15% absent any other documented upgrades. A meta-analysis of energy conservation studies between 1975 and 2012 indicated that implementing energy efficiency measures without behavioral-change (feedback) mechanisms actually led to an increase in energy consumption over time because consumers become less

concerned about the need to conserve (Delmas et al., 2013). "Programs can achieve greater impact and deeper savings by incorporating insights from social and behavioral sciences" (Mazur-Stommen & Farley, 2013, p. v). To achieve the goals of utility efficiency programs, the inclusion of learning and pro-environmental behavioral change for energy consumers is important.

Improving environmental literacy in schools not only has an impact on student learning and school energy consumption, but it can also have a positive impact on student homes and surrounding communities in terms of spreading awareness and encouraging behavioral changes. Young people generally are open to environmental topics and often hold pro-environmental beliefs more strongly than do their parents (Allen et al., 2013; Coffey & Joseph, 2013; Craig & Allen, 2014). Similar to seat-belt, anti-smoking, and anti-bullying campaigns deployed in schools (e.g., Ad Council, 2013; National Highway Traffic Safety Administration, 2008; Stuart-Cassell et al., 2011), students are capable of disseminating environmental knowledge and discussing related topics at home. With knowledge, experience, and tools, students may be able to influence energy usage by their parents and other household members. Recognizing this potential, some educational programs have focused on reaching student homes through the school (e.g., National Energy Foundation's Think!Energy Program and the Resource Action Program's Living Wise) as well as on saving energy in the school (e.g., ASE's Green Schools program).

The purpose of this case study is to longitudinally track the effects of behavioral change intervention in one K-3 elementary school in terms of increased student knowledge and reduced energy consumption at school and in student homes. The focal school participated in a statewide "green" competition among K-12 schools in a rural south-central US state. Participating schools

chose their own projects. The focal school elected to focus on energy efficiency, although the statewide competition was not energy or efficiency specific. Environmental competitions among schools can be effective at encouraging conservation behaviors, including energy conservation (Bulman & Ehrendreich, 2010). Competitions that promote community-level energy conservation can also help households' lower energy bills and reduce carbon emissions (Melillo et al., 2014).

Understanding the linkages among energy use, emissions, and climate variability is challenging for schools, parents, and students. Interventions associated with learning about energy consumption using systems-level thinking (Forrester, 2009) have the potential to show students how efficiencies can be used to make positive change. A systems-level approach includes identifying a concept or problem, engaging in an action relative to the concept or problem, and observing the result in order to guide future decisions, all set within a temporal context of feedback networks (Forrester, 2009). In this case study, students engaged in system-levels thinking at school through the implementation of curriculum-based learning that: (1) introduced what energy is, how it is produced, and how it is measured (i.e., the concept), (2) provided knowledge and skills as to the actions students could take to be more efficient by reducing energy consumed (i.e., action), and (3) reported energy savings and directly linked these savings to reducing CO₂ emissions (i.e., results).

The outcomes of interest in this case study were (1) increased student knowledge in terms of environmental literacy as related to energy, and (2) decreased energy use in students' homes and in their school. The goal of the intervention was to create a learning environment that followed STEM (science, technology, engineering, and math) guidelines to help students gain knowledge and skills related to energy consumption, and apply the newly acquired knowledge

and skills to measurably reduce energy usage. The study used a longitudinal design to examine student energy knowledge, energy usage at student homes, and school energy usage.

4.2.1 Knowledge acquisition and environmental literacy

Student knowledge about energy, energy alternatives, carbon emissions, and energy use has the potential to influence future generations in terms of resource and climate issues. Students gain knowledge from a variety of interpersonal sources including peers, teachers, principals, and parents (Allen et al., 2013; Schelly et al., 2012). The home and the school are two of the most salient sources from which young people gain the information they need to build knowledge (Karliner, 2005; Warren & Wicks, 2011). To-date, however, detailed interventions that combine experiential learning about energy usage education in the classroom, throughout the school, and into student homes have not been widely utilized or effectively tracked. Our goal is to join other researchers and address the gap between general energy awareness and actual behaviors (e.g., Gupta & Ogden, 2009; Kollmuss & Agyeman, 2002; Mahone & Haley, 2011; Pickett-Baker & Ozaki, 2008; Unsworth et al., 2013) in order to quantitatively examine whether and how student knowledge can lead to energy conserving behaviors. In this study, we focus on energy usage in the form of electricity use.

Some secondary school students have a high level of awareness about general topics, such as renewable energy and energy efficiency (Aktamis, 2011) However, actual knowledge may be limited or basic due to a variety of reasons, including limited exposure to information at school, inadequate educational resources, limited teacher knowledge, the politicized nature of many energy-related topics, and lack of information or agreement within the home about energy-related issues. The quality of information related to conservation and frequency of exposure is less than for other topics covered in schools (Karliner, 2005; Owens, 2005). In a quantitative

study of the environmental language used by young children, Owens found that implementation of a standardized curriculum in elementary schools was "detrimental to pupils' environmental language acquisition" (p. 324). According to www.corestandards.org, common-core standards that have been adopted in the majority of states include literacy but environmental literacy is not explicitly included. Differences in environmental perceptions and actions, tend to fall along partisan lines (Coffey & Joseph, 2013), making it challenging to diffuse knowledge about energy and conservation in U.S. schools. States and even communities vary in what they teach, sometimes for political reasons. For example, lawmakers in Wyoming blocked the adoption of science curriculum treating anthropogenic climate change as a fact (Miller, 2012) despite widespread scientific consensus on this issue (Melillo et al., 2014). Resources and teacher training on environmental education is generally inadequate, and a concentrated effort to educate students about quantifiable energy usage and efficiency is rare (Karliner, 2005; Owens, 2005; Schelly et al., 2012). In addition, numerous studies have found that adult knowledge and awareness about energy are relatively low (e.g., Craig & Allen, 2013; Langevin et al., 2013).

Despite these challenges, it is possible for elementary students to learn about energy and apply what they learn by engaging in energy conservation behaviors at school and in their homes. Students tend to interpret environmental concepts in terms of the limited knowledge that they already possess (Lourdel et al., 2007). Therefore, in our intervention, exercises were discussed using language and concepts that were concrete, easily accessible, and actionable (Pelletier & Sharp, 2008). For example, grade-school students can turn on a light switch at home or school and understand that electricity is being consumed. Students can push the power switch on their video game consoles and see the device turn off. Research has shown that students are fully capable of processing information about complex systems (Forrester, 2009). Our

intervention framed energy usage for students in terms of kilowatt-hours (kWh), the unit of measurement for electricity. Once students understand this unit they can engage in concrete activities, such as reading their home's electricity bill. With additional knowledge, students can move to more abstract thinking (Lourdel et al., 2007; Segalas et al., 2009). Accordingly, we offer the following hypothesis regarding student acquisition of knowledge in terms of energy usage:

Hypothesis 1: A combination of classroom and experiential exercises at school and home about energy usage can increase student knowledge about energy.

4.2.2 Student home and school energy consumption

Due to high energy costs and limited discretionary income, knowledge related to energy efficiency can be especially important for students living in less affluent households. Langevin et al. (2013) conducted an energy awareness and behavior study with occupants who lived in government assisted housing. They found only 21% of those surveyed recalled getting education or information about being energy efficient at any point prior to the survey. Similar to Langevin et al., the majority of student households included in the current study received government assistance related to income-level, with over 70% of the students in the participating school receiving free or reduced-priced lunches. Access to energy efficiency is unequal due to relatively high out-of-pocket costs for low-income households (Craig & Allen, 2014; York et al., 2013) despite the obvious benefits of reducing the burden of energy bills. For example, even CFL bulbs that are discounted as part of an efficiency program at a local retailer can cost three to four times more than incandescent bulbs.

Younger people are significantly more likely to perceive alternative energy use favorably (Craig & Allen, 2014) and can influence their parents' energy use behaviors. Allen et al. (2013) demonstrated that young people between the ages of 12 and 17 felt global warming should be a

priority of the U.S. president at levels higher than did their parents. Although parental environmental attitudes and behaviors certainly influence their children, sometimes the reverse is also true. Specific to energy savings, Bulman and Ehrendreich (2010) demonstrated that a national environmental initiative among 5,000 K-12 schools resulted in a 32,000 megawatt-hour (MWh) residential usage reduction. Considering the past effectiveness of students at changing their parent's behaviors, we pose the following hypothesis:

Hypothesis 2: Students can help reduce their household's energy consumption.

Students also can influence energy consumption in their school. In addition to engaging in simple activities such as turning off the lights or powering down computers when not in use, students can provide feedback mechanisms to remind all school occupants to engage in energy conserving behaviors. Cross et al. (2010) conducted a case study at Poudre School District in Colorado. Through a combination of efficiency measures and transformational behavioral interventions, the Poudre School District lowered its energy consumption to a level 37% below the state average. Our focal school district had previously implemented energy efficiency measures within the schools, but had not focused on transforming occupant behavior. Research suggests students can drive environmental and social initiatives in their schools and at their homes when they are empowered to do so (e.g., Bulman & Ehrendreich, 2010; Cross et al., 2010; Karliner, 2005; Schelly et al., 2012). For instance, the Green Schools program administered by the Alliance to Save Energy saved 15 K-12 schools an average of \$7,700 due to occupant behavioral change (United States Department of Energy, 2002). We hypothesize that as more students are engaged in monitoring energy use and providing real-time feedback to decisionmakers in their schools, energy conservation will increase:

Hypothesis 3: Energy consumption at the school will decrease over the course of behavioral change intervention.

4.3 Materials and methods

4.3.1 Procedure

The study took place over a six-month span that coincided with a K-3 school's participation in a statewide "green" competition where schools selected their own projects, not all of which focused on energy. The study was conducted in cooperation with the district superintendent, district energy manager (the assistant principal), and school principal. The primary researcher attended a recruitment meeting prior to the project and received approval from the district superintendent and district energy manager to direct the project and conduct the study. The primary drivers for recruitment of the focal school were (1) the socio-economic make-up of the school, with over 70% of students receiving government assistance on lunches, and (2) the presence of a strong champion at the school-level. The district energy manager was the primary champion in the school during the project. Although located in a rural southern state, the case shares demographic characteristics with other school districts around the U.S.: nationally, approximately 31 million out of approximately 49 million public school students (63%) are eligible for free or reduced priced meals, a number than increases as poverty levels grow (United States Department of Agriculture, 2013; United States Department of Education (USDE), 2013a, 2013b).

The intervention started in month one with a kick-off assembly to announce the project and convey school and community support to the students. The district energy manager (assistant principal) and the primary researcher addressed the students about the project's aims. The city mayor and a local business leader attended to share a message of support, and the event was

covered by the local newspaper. A wrap-up assembly was held in month six to announce the results, and to film a short video of the students for submission to the statewide competition. The city mayor and local business leaders once again attended to congratulate the students and to offer additional messages of support and encouragement.

The topical structure of the intervention was loosely derived from Neale Godfrey's (2009) book, "Eco-Effect: Greening of Money." This interactive book focuses on the economic impact of a young person's pro-environmental behaviors at home and school, and encourages parents and teachers to work with their students by providing at-home and related classroom exercises. Modifications of Godfrey were necessary due in part to the younger target group (third grade students as opposed to middle-school students), and the focus on electricity reduction as opposed to conservation generally. While we simplified some language due to student age, the complex interconnectedness of the electricity system at home and at school remained intact.

A paper-form survey was administered by the primary researcher to 80 students from four third-grade classes in month one and again in month five to assess knowledge about energy usage. The pre-test consisted of 12 items and the post-test consisted of 14 items. Two additional post-test questions at the end of the survey were designed to provide programmatic information to the participating school, including "Who teaches the most about saving electricity?" Both surveys took students approximately 20 minutes to complete. Only matched pairs of pre- and post-tests (n = 63 out of a total of 80 students) were considered in the data analysis. Months two through four included classroom instruction and energy assessment exercises at the school, facilitated by the primary researcher (see Table 1 for the topics and exercise covered each month). Approximately one hour was spent with each student in classroom learning and experiential exercises in months two through four. Take-home exercises were assigned in each of

these months covering the same topics as the school exercises. Take-home assignments tracked home energy consumption each month by asking students to report kWh usage statistics for their month's electricity bill for the current and previous year (e.g., December 2013 and December 2012 kWh consumption were reported). Students also responded to open-ended questions asking about best-practices to save energy at home and at school.

Schools tend to have consistent attendance schedules from year-to-year, although month-to-month students may not be present the same number of days (for example, due to December holidays). Whether the school is open and students are in attendance directly impacts energy consumption patterns at school and in student homes. The year-over-year longitudinal analysis was utilized so as to avoid any month-over-month variability during the study period.

As noted, feedback is considered an integral component in efforts to promote energy efficiency (Craig & Allen, 2014; Delmas et al., 2013). During the intervention, mechanisms were put in place for students to provide feedback at home and at school, which would influence adults and other students to participate in taking energy saving actions. For example, students were given stickers during walk-through experiential exercises at school to put next to areas where energy waste was occurring, and signs were posted throughout the school to explain the project and the meaning of the stickers. Stickers were placed next to light switches and on unneeded or unused appliances. Students repeated this exercise at home. While the district energy manager was the official champion, the participating students and teachers also communicated with their peers about the project and garnered additional support within their school. Students were also encouraged to adjust the thermostat both while in the classroom and when the classroom was empty to maximize savings. School policy was put in place and communicated throughout the school to adjust classroom thermostats at the end of the day, with

facilities staff responsible for thermostats in common areas. Students also provided open-ended feedback on take-home assignments with suggestions about saving energy at home and at school, which was shared with teachers and school officials. By making the results of the study available to students at school via an assembly, sending the results home with the students, and sharing the results with local civic and governmental organizations, the researchers helped put in place a mechanism through which students could communicate their understanding and actions.

4.3.2 Student sample

As mentioned, 63 out of the 80 students completed both the pre- and post-tests (79%). Results from students who did not complete both tests were not included in the results. Individual student information was not collected because of school policy and privacy concerns. Release forms were signed by parents of participating students. The third-grade students who participated in the study were eight or nine years old on average. The school principal shared that there were 426 students who attended the school, that more than 70% of them received free or reduced priced meals, that approximately 20% had disabilities, and that many were English as a second language learners. Public records indicated that the district had about 4000 students in attendance at K-12 schools. USDE (2013a) statistics indicate that about 12 million students attend rural schools, and that the focal school's poverty level was similar to towns or cities having high numbers of students receiving free and reduced priced meals.

4.3.3 Measures

Fredricks et al. (2011) found that there were limited instruments that measured both the attitudinal and cognitive dimensions of elementary students in relation to their behaviors at school. To the best of our knowledge, a multi-dimensional instrument that taps both attitudinal and cognitive elements related to energy efficiency does not exist. Therefore, original questions

were designed for this study. Two questions gauged the cognitive dimension of student knowledge during the pre-test and post-test. Students were asked to pick the correct answer from four possible multiple-choice options. Student knowledge about electricity consumption at home was measured with two single-item measures consistent with prior environmental literacy research on middle school and high school students (e.g., DeWaters & Powers, 2011): "What uses the MOST electricity at home?" Possible responses included (1) air conditioner and heater, (2) video games, (3) washer and dryer, and (4) lights (#1 is the correct answer). Knowledge about the kWh was measured with the question, "The distance you ride to school is measured in _______?" Possible responses included (1) therms, (2) kilowatt-hours, (3) volts, and (4) degrees (#2 is the correct answer).

Student take-home assessments were designed to engage students and their parents in learning about how energy is measured and consumed at home. Additionally, we hoped that this elevated level of engagement would promote household behavioral change. Each of the three take-home assessments asked students to provide the kWh consumption for their home in the current and previous year. The first take-home assessment was conducted in November, where students analyzed electricity billing data from the previous month (October). Students were also asked to walk through their home and answer questions about the number and type of lights bulbs used, the use of lights, the number of electronic devices, and the use of electronic devices in the home. For example, one question about the use of lights was, "How many rooms that had the lights turned on were unoccupied?" A sample question about the use of electronic devices was, "How many electronic devices were turned on that were not being used?"

The second take-home assessment was conducted in December, and students again analyzed the electricity billing data from the previous month (November). The second

assessment asked students about the heating and cooling of their home. Sample questions included: "On what temperature is your thermostat set?" and "Do your parents turn the temperature on the thermostat down when they leave home in the winter?" The first two takehome assessments also included open-ended questions about the best way to save energy at home. The third take-home assessment was conducted in January (December billing data), and included an open-ended question about the best way to save energy at school.

Student energy consumption was reported on take-home assessments from resident electricity bills from the current and previous year for October, November, and December. Electricity consumption was measured in kWh. According to the EIA (2009), 50% of residences in the focal census division used electricity as the primary heating fuel source, and 33% of residences used electricity as a secondary heating fuel source. School energy consumption was reported directly from school electricity bills for the same months (current and previous year) as the students reported. The focal school used electricity as the primary heating fuel source.

In order to identify whether or not the intervention was associated with reduced energy consumption it was important to consider climatic influence. Historical temperature data in Fahrenheit (° F), monthly heating degree days (HDDs), and monthly cooling degree days (CDDs) were retrieved from National Oceanic and Atmospheric Association (www.ncdc.noaa.gov) for the local airport reporting station. HDD and CDD are measures of how much energy is needed to heat or cool a building given local temperature conditions, where "A degree day indicates that the daily average outdoor temperature was one degree higher or lower than some comfortable baseline temperature" (EPA, 2014). The baseline temperature commonly used is 65 ° F. Degree days are versatile and effective indicators because of the relationship between temperatures and energy consumption (Mourshed, 2012; Timmer & Lamb, 2007).

Weather normalization neutralizes the impact of anomalously hot or cold days on energy consumption, and is commonly used by utility companies throughout the country, including states in the focal region (Marple, 1995; Cross, 1996). The calculation considers heating consumption relative to baseload, which consists of average and constant (non-fluctuating) electricity consumption (see Nelson, 2008). Weather normalization is used to account for energy consumption variability based on HDDs or CDDs. There were 37 CDDs in October 2013, 33 CDDs in October 2012, 8 CDDs in November 2013, and 2 CDDs in December 2012. We ran paired sample T-tests for year 2012 and 2013 for the months of October, November, and December to determine if there was a significant difference in kWh usage per HDDs and CDDs. There were no significant findings for CDDs, so this was not included in the subsequent analysis.

4.3.4 Statistical analysis

To examine Hypotheses 1, we computed frequency data to gauge knowledge levels from the pre-test and post-test. To investigate Hypotheses 2 and 3, it was necessary to calculate a weather adjusted kWh value (normalization) to take into account space heating consumption. We first divided kWh consumption for each month by HDD. Based on a national average, we assume that residential baseload (not accounting for heating and cooling equipment) is 53.4% (Hendron and Engebrecht, 2010). Accordingly, the overall baseload consumption for the sample was calculated by multiplying kWh consumption by 53.4%. Next, we multiplied kWh / HDD by the percentage of electricity for space heating, or 46.6%, to get heating kWh / HDD. Finally, the average HDDs for both years were multiplied by the weather factor (kWh / HDD), which was then multiplied by the baseload value to provide the weather adjusted kWh. Percentage changes in weather-adjusted kWh between 2012 and 2013 are reported for October, November, and December (see Table 1).

4.4 Results

Hypothesis 1 investigated the impact that traditional classroom teaching and experiential learning at home and school have on student knowledge levels. For the first knowledge question, "What uses the MOST electricity at home," students exhibited an increase in correct responses. On the pre-test completed by 63 students, 17.46% (n = 11) of the students answered "heater and air conditioner" correctly, compared to 52.38% (n = 33) on the post-test. The second knowledge question asked students to correctly identify the unit of measurement for electricity consumption. On the pre-test, only 9.52% (n = 6) of the students correctly identified a kWh. However, 76.19% (n = 48) of the students answered correctly on the post-test. Hypothesis 1 was thus fully supported.

Hypothesis 2 stated that students could positively impact energy consumption at home. This hypothesis also was fully supported. We ran paired sample T-tests comparing kWh / HDD to determine whether there was a significant difference in consumption between years 2012 and 2013. There was not a significant difference between kWh / HDD between October 2012 and October 2013, the month prior to the intervention. While the results were not significant, there was an increase of 9.12% in weather adjusted kWh between October 2012 and October 2013. The use of HDD controlled for extreme temperatures, and the weather data were collected at the same point in time in both 2012 and 2013 to ensure the integrity of the data (EPA, 2014). The first educational intervention took place the first week of November 2013, making October the base month in that no formal educational information about energy consumption or efficiency was provided. Following the first educational intervention in November 2013, we saw a significant change in kWh / HDD in student homes (t = 6.707, p < .001, n = 25, SD = .372) between November 2012 and November 2013, with a reduction in weather-adjusted kWh of

15.93% year-over-year. Between December 2012 and December 2013, there was a significant difference in kWh / HDD in student households (t = 8.181 p < .001, n = 43, SD = .636), with a year-over-year weather-adjusted kWh reduction of 13.72%. Post-hoc paired sample T-tests were run to compare students who responded correctly to knowledge questions from Hypothesis 1 and reported energy reduction with students who answered incorrectly and reported energy reduction. We found no significant difference between the groups.

To examine Hypothesis 3, the same procedure was used to prepare the school kWh usage for analysis that was used for student households. For the school, we had only two unique values at two points in time for the focal months of October, November, and December, so we were unable to run a difference test. The school saw an increase of 4.97% in weather-adjusted kWh consumption between October 2012 and October 2013, a 10.59% decrease between November 2012 and November 2013, and a 30.67% decrease between December 2012 and December 2013. Hypothesis 3 was thus fully supported as well: energy consumption at the school decreased over the course of the intervention.

4.5 Discussion

In this study, third-grade students learned what a kWh was and how to correctly identify and manage electricity use at home and at school (e.g., by turning off lights). Elementary students are clearly able to engage in systems-level thinking when given the opportunity to engage with hands-on and creative instruction (Forrester, 2009). Indeed, based on previous studies, the students exhibited a greater understanding and ability to apply energy-related concepts than many adults (e.g., Craig & Allen, 2014; Langevin et al., 2013). The students demonstrated a significant increase in their environmental literacy (see DeWaters & Powers, 2011).

What is most important is that students can use what they learn at school to make positive changes in their homes and schools, whether through their own behaviors or through their influence on adult behaviors through direct and active feedback. Curriculum-based learning focused on environmental literacy, and the use of experiential exercises was associated with decreases in weather controlled electricity consumption. The focal school facility, which had engaged in multiple energy efficiency activities regulated by the state public utility commission and administered by the local utility company, saw additional significant reductions in weather-controlled electricity consumption. While energy efficiency measures (such as lighting retrofits) had been implemented in the past there were no active projects at the school during the 2013 project year. Furthermore, the focal school had never used utility incentives for the maintenance or upgrade of heating and / or cooling equipment.

As seen Table 1, in November and December there was a dramatic increase in HDDs from year-to-year that would necessitate increased consumption of electricity. By differentiating baseload and weather-sensitive consumption, we were able to control for weather variability and demonstrate the success of the interventions in terms of energy savings. Both the school and the students saw a decrease in actual and weather controlled kWh in November despite the month-over-month HDD increase from October to November and the year-over-year increase in November. In December, the school was able to decrease actual kWh consumption in the face of even colder weather, but the student homes saw an increase in actual kWh consumption. Post-hoc analysis was conducted to put this finding in perspective (see Table 2). Using electricity consumption and consumer statistics retrieved from the United States Energy Information Administration (EIA, www.eia.gov), we were able to demonstrate that in October of 2012 and 2013 (the control month), state residents experienced a comparable increase in electricity usage.

For December, however, average residential consumption increased by 21% from the prior year but only 7% for our student households.

Energy reductions can be achieved through various economic, technological, and behavioral mechanisms including setting higher energy costs, promoting efficiency upgrades, setting standards or mandates, providing incentives, and using persuasive messaging (Craig & Allen, 2014; Gilleo et al., 2014; Jessoe & Rapson, 2014; Wilson & Dowlatabadi, 2007). A combination approach may be used. For example, Jessoe and Rapson (2014) found that residents who received information about saving energy during periods of increased costs were significantly more likely to lower their consumption than those who did not receive information. Absent information about energy savings, residents did not significantly alter their consumption during periods of higher costs. Efficiency upgrades in residences that are mandated or incentivized often miss energy reduction targets absent control mechanisms such as feedback, messaging, or automated technologies (Craig & Allen, 2014; Delmas et al., 2013; Greening et al., 2000; Suter & Shammin, 2013; Wilson & Dowlatabadi, 2007). An integrated approach that incorporates behavioral interventions such as "nudging" or providing rich feedback can help overcome energy savings shortfalls (Greening et al., 2000; Suter & Shammin, 2013; Wilson & Dowlatabadi, 2007). Stand-alone residential behavioral interventions with rich feedback about individual energy consumption maintains relatively persistent savings during and after interventions and are cost-effective (Alcott & Rogers, 2014). While economic and technological mechanisms for efficiency are widely deployed and cost-effective (Gilleo et al., 2014), recently more robust evaluation, measurement, and valuation (EM&V) techniques have shown that behavioral programs can be cost-effective as well (Alcott & Rogers, 2014; Mazur-Stommen & Farley, 2013). For both residences and school districts, in cases where funds are not available for upgrades, where local or state governments are unwilling to set policy, or where the utility provider is constrained in terms of rate increases, there is growing support that behavioral interventions are a viable and cost-effective alternative (Alcott & Rogers, 2014; Craig & Allen, 2014).

Normative messaging and social pressure (including "nudging") from significant others can drive behaviors (Cialdini, 2003; Thaler & Sunstein, 2008). Children are arguably among the most significant others in a parent's life, and by placing normative pressures on their parents through constant, direct, and active feedback, it is not surprising that the reported energy savings were achieved. This study was designed in a manner that allowed students to change as well as influence energy consumption behaviors through their actions at home and school. In our study, students were empowered to be a feedback mechanism in two primary ways. First, they were given stickers that were placed around the school, and most importantly, placed around their homes next to light switches, thermostats, and anything else that the students perceived to waste energy. Second, the students engaged with their parents for the three months of the project to analyze their household energy bills as part of take-home assignments. Students were an active and direct feedback source to adults. "Nudges" took place between teachers, among students, and at home where parents were influenced by their children. Future studies might investigate, for example, whether energy savings are greater in homes with access to real-time energy information from smart meters where young residents have been trained in energy efficiency. The integration of energy efficiency technologies and behavioral change training has the potential to increase energy savings beyond either independently (Mazur-Stommen & Farley, 2013, p. v).

In our study, adults (parents, teachers, and administrators) played a role in the observed energy savings by engaging in conservation behaviors throughout the school and in homes. Students were not only empowered to make changes themselves (e.g., turning off the lights, turning off computers when not in use), but feedback activities were designed to inspire action among adults. The level of electricity savings in student homes and at the school facility were encouraging. At the same time that student knowledge and experience increased, energy consumption dropped at levels consistent with past residential behavioral research (Darby, 2006).

4.6 Conclusion and policy implications

Our study demonstrates how behavioral interventions can engage students and adults. Our data show verifiable energy savings in both the school and the home. While the majority of behavioral programs have not undergone EM&V (Mazur-Stommen & Farley, 2013), programs that provide rich feedback have demonstrated persistent energy savings over time (Alcott & Rogers, 2014). Our findings with regard to energy savings are consistent with prior research (e.g., Bulman & Ehrendreich, 2010; Cross et al., 2010). For instance, the Alliance to Save Energy deployed a national environmental initiative among 5,000 K-12 schools (Bulman & Ehrendreich, 2010) that resulted in a total reduction of 32,000 megawatt-hours (MWh). The energy savings at our focal school were comparable. Despite the positive impact experienced by schools and communities that engage in organized efficiency initiatives, such as the one described in the current study, concentrated efforts to educate students about quantifiable energy usage and efficiency are rare.

Behavioral change related to energy use and conservation requires a number of components, including knowledge, motivation, ability, and reinforcement (Kollmuss &

Agyeman, 2002; Unsworth et al., 2013). Statewide school competitions to reduce energy usage are promising. In order for behavioral change to occur and endure, however, efficient conservation behaviors must be continually reinforced until they become habits. Recurring social support within communities can help reinforce energy-related behavioral change (Staats et al., 2004). This was evidenced in the current study, where participation by the city's mayor and a prominent local business leader provided reinforcement as well as mechanisms to hold school officials accountable.

Recent research demonstrates that adult awareness and knowledge about energy and climate issues remain low (Craig & Allen, 2014). Unless elementary students are exposed to these concepts at home or at school, they will lack the knowledge and skills needed to address these issues as consumers and citizens. Encouragingly, and also consistent with prior research (Allen et al., 2013; DeWaters & Powers, 2011), the study demonstrated that students can increase their environmental literacy, and suggests students can change their own behaviors, and disseminate what they learned throughout their school and into their homes.

4.6.1 Policy implications

Currently, energy use and conservation are largely topics covered only during competitions or incentive programs, if at all. School energy conservation programs should be part of public education. Expanding these programs requires policy support from various government levels and agencies. High school energy bills deplete scarce school operating funds that might otherwise be directed toward instruction or other purposes. School building retrofits should routinely incorporate behavioral education and change components. Energy saving ideas learned in the classrooms carry out into the community to help families manage their energy use.

Policies related to school curriculum on energy and deployment of energy efficiency funds thus have implications for the financial health of schools, households, and communities.

Clearly, more schools and students remain to be reached. The curricular materials and other resources already exist. The first author developed a workable curriculum targeted to third-grade students loosely based on Godfrey's (2009) work. The EIA (www.eia.gov/kids) provides information for young children, the U.S. Department of Energy (www1.eere.energy.gov) provides lesson plans and activities for K-12 students, and the National Energy Education Development Project (www.need.org) provides information for older students. Numerous pilot projects with students have shown successful energy savings (e.g., United States Department of Energy, 2002). However, the inconsistency with state- and federal-level policy, and the policy battle over the deployment and content of common-core standards for elementary students, has created a major hurdle for systematically deploying curricula on energy and conservation. In many schools, student literacy suffers because material not in the common core becomes discretionary and unsupported by standard materials such as text books available to the teaching staff (Bean et al., 2012).

In sum, behavioral change campaigns implemented in schools may be a low-cost mechanism for influencing discretionary energy consumption behaviors. Perhaps more importantly, the long-lasting impact of behavioral change through student learning might empower future generations to better meet impending environmental challenges.

4.6.2 Limitations and next steps

The current study was not without limitations. The study took place in a single school in a rural Southern community in the U.S. Demographic information related to household type, ownership, occupancy, and home heating source were not readily available. The lack of

availability to household baseload to calculate weather adjusted kWh consumption is also a limitation. However, the socio-economic make-up of the students in terms of meal assistance, disabilities, and English as a second language learners, is consistent with many school districts around the country. The three-month duration is another limitation of the study. Clearly a longer time period would be desired. By focusing on education, the foundation for prolonged change was put in place but additional evaluation is needed. Other limitations are the small sample size and the limited number of children who turned in the homework recording home kWh use.

Certainly, a stronger research design would have included a control group. However, it can be difficult to gain access to elementary students to conduct a project with intensive interventions, as was the case here. Gathering longitudinal energy-use data from the families appeared the best option. If some children had been placed in a control group our final number of paired responses would have been even smaller. Our study also was confined to third-grade students; results may vary for other student age groups. Despite such limitations, our results are consistent with other studies and support our policy recommendations.

Needed now is more systematic deployment and rigorous evaluation of energy-related behavioral change campaigns within homes, schools, and communities. A study such as this one could be deployed at multiple schools across several states. Future research can address this study's limitations by increasing the sample size, providing a longer intervention, and assessing the persistence of energy savings across time. Such large-scale testing and intervention could be stimulated by funding through various government efficiency programs. Federal and state policymakers should consider moving such initiatives forward and partnering with research universities to investigate the use of school based energy conservation programs on individual, school, and community behavioral change.

4.7 References

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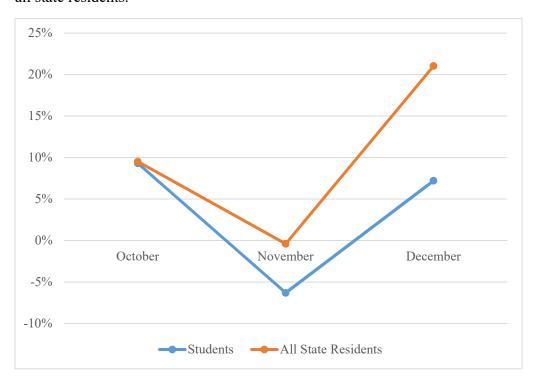
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4.8 Figures

Table 1. Topics covered, student exercises, energy savings for weather adjusted kWh, heating degree days.

Month	Topics Covered	School Focused Exercises	Home Focused Exercises	School weather adjusted kWh % Change compared to previous year	Student weather adjusted kWh % change compared to previous year	School weather adjusted kWh consumption 2013 / 2012	Student weather adjusted kWh consumption 2013 / 2012	Heating Degree Days 2013 / 2012
November	kWh Consumption – Lighting and Appliances	Classroom instruction; Walk- through assessment of school halls, cafeteria, and auditorium	Lighting and appliance assessment; Electricity Bill Analysis for October 2012 and 2013, placed feedback stickers	4.97%	9.12%	19,179 / 20,223	1085 / 994	209 / 208
December	kWh Consumption – Heating and Air Conditioning	Classroom instruction; Walk- through assessment of individual teacher classroom thermostat, air filters, doors, windows, lighting, and appliances	Heating and air conditionin g assessment; Electricity Bill Analysis for November 2012 / 2013	- 10.59%	- 15.93%	18,257 / 20,467	843 / 1006	625 / 496
January	kWh Consumption – Kitchen and Review	Classroom instruction; Walk- through assessment of school kitchen	Electricity Bill Analysis for December 2012 / 2013	- 30.67%	- 13.72%	15,875 / 23,002	1264 / 1471	831 / 525

Table 2. Raw kWh consumption % change between 2012 and 2013 comparing focal students and all state residents.



Chapter 5: Discussion and conclusion

5.1 Discussion

The body of this study provided insights into how micro-level pro-conservation interventions including experiential learning and EE programs can be utilized to address macro-level issues such as policy and GHG emissions. Chapters 2 – 4 were closely interrelated in taking a systems approach to better understand the problem of GHG emissions and climate change. Energy utility organizations and regulatory bodies have utilized EE program offerings as a potential action to reduce residential electricity and generation demand. Consistent with the environment / social systems approach posited by Bapat (2005) discussed in Chapter 1, the impact of EE programs was quantitatively analyzed in Chapters 2 and 3 over time to provide useful feedback for future action. The study deployed a survey instrument in Chapter 3 and a behavioral intervention in Chapter 4 to inform actionable pro-conservation strategies to mitigate anthropogenic induced climate change related to residential electricity consumption.

Chapters 2 – 4 of the study sought to gain a clearer understanding of how climatic interactions with individual electricity use could be used to inform pro-conservation, behavioral interventions. The pro-conservation efforts of interest in the study were EE efforts in terms of electricity reduction in Chapters 2 and 3, EE efforts in terms of incentive and indirect costs in Chapter 3, and experiential learning interventions in Chapter 4. The focal stakeholder groups were the energy utility organization – the primary CO₂ emitter globally (Heede, 2014) – and the residential electricity consumer – the primary consumer in the US (EIA, 2015c). The study examined the relationships CDD and HDD had with electricity consumption on the national-(Chapter 2) and state-levels (Chapter 3), and the relationship HDD had at the local-level (Chapter 4) to gauge the influence of climatic variability. While not causal, a major contribution of the current study was to integrate natural and social sciences related to GHG emissions /

mitigation along a macro-micro continuum. When considering climatic variability and societal interaction, one cannot be considered without the other. Consistent with Bapat (2005), the study quantified both environmental and societal (i.e., pro-conservation) constructs. The utilization of behavioral interventions that quantify actual interactions between local climatic conditions and natural resources can be used to make complex social / environmental relationships more easily understandable to stakeholders

5.1.1 Chapter discussion

Chapter 2 examined the predictors of CO₂ emissions and residential electricity consumption across the US. The two most significant contributors to CO₂ emissions explained 97.2% of the variability, with coal generation in first step of the model explaining 83.8% of the variability and residential electricity consumption explaining an additional 13.4% in the second step. The residential sector was the most salient contributor to CO₂ emissions; industrial consumption accounted for only .08% of the variability in CO₂ emissions from the electric industry and commercial consumption was not significant. Residential electricity consumption was significantly related to CDD in 33 states, HDD in five states, and EE kW savings in 34 states. The most significant and strongest relationships tended to be between CDD and electricity consumption, particularly in the Southeast and East US. The majority of these relationships were positive.

Several negative relationships emerged in the Northwest US, however, where CDDs increased as consumption decreased (e.g., Idaho, Oregon. Washington). Research Question 3 provided some guidance on the counterintuitive negative correlations between CDD and residential electricity consumption. In Oregon, for instance, EE kW savings and electricity consumption were positively correlated and decreased together throughout the study period,

where EE was the only variable in the regression model. During the study period, however, CDDs significantly increased in Oregon, hence the negative relationship. When EE kW savings per resident explained variability in consumption in other states, however, the general trend was a negative relationship where EE kW savings per resident decreased while consumption increased towards the end of the study period.

All relationships were positive where CDD was a significant predictor in the regression model at the state-level. With temperature and CDDs predicted to increase (Ingram et al., 2013; IPCC, 2014), electricity demand is also predicted to increase (McFarland et al., 2015; Mideksa & Kallbekken, 2010). Chapter 2 provided historical support, demonstrating strong positive relationships where CDDs and residential electricity consumption increased together. The observed salient relationships and future models suggest that of the independent variables in Chapter 2, CDD may be of greatest concern to increased electricity production needs and the related GHG emissions in the future. The mixed results and observed ineffectiveness of EE kW savings at reducing residential electricity consumption in the study magnify the importance of policy and behavioral mechanisms to reduce GHG emissions. The findings of Chapter 2 addressed the knowledge gap of relative effectiveness of state-level EE programs, and also the impact of increased climatic variability not addressed by deemed savings models.

There were observed positive relationships between CDD and residential electricity consumption in the Southeast US in Chapter 2, and projections suggest increased temperature, extreme events, and electricity demand in the region (Ingram et al., 2013; IPCC, 2014; McFarland et al., 2015) Accordingly, Chapter 3 focused on a state in the Southeastern US. For electricity consumption allocated to heating, the only significant predictor was non-incentive, indirect costs with a two-year lag. For kWh residential consumption related to cooling, however,

a two-step model that included non-incentive, indirect EE costs with a two-year lag and CDDs together explained 33.6% of the variability. Consistent with several states in the Southeast in Chapter 2, CDDs shared a positive, significant relationship with electricity consumption per resident, and HDD was insignificant. In the focal state, actual kW savings from EE and direct, incentive costs were not significantly related to electricity consumption. This is consistent with the Delmas et al. (2013) meta-analysis, in that incentives absent communicative mechanisms may be ineffective. However, the significance of non-incentive EE costs suggest that it may be marketing and / or other personnel related costs that are influencing resident electricity behaviors. The two-year lag suggests it may take consistent spending over time to adequately address pro-conservation behaviors. Like many states in Chapter 2, however, persistence of EE offerings declined in the residential sector, and consumption steadily increased during later years of the study period.

Chapter 3 also explored how EE program awareness and participation were related to resident characteristics, including perceptions of energy utility organization motives and support for GHG reducing policy. Residents who are aware of EE program offerings are significantly more likely to participate in EE programs than those who are unaware or misinformed. However, low levels of awareness in EE by residents (Craig & Allen, 2014; Langevin et al., 2013) still remain a challenge to participation in EE. The gradual reduction in residential program offerings throughout the study period in most states may have reduced the likelihood of increased knowledge and awareness about EE programs, and may be a possible cause of low awareness levels about EE.

Residents who were aware of EE programs were also significantly more likely to perceive utility motives for offering EE programs as positive compared to those who were

unaware or misinformed, and were more likely to support government subsidies for EE than those who were unaware. However, residents who were unaware of EE program offerings were more supportive of clean energy use by the energy utility organization. It may be that the lack of awareness about EE offerings influenced low levels of trust of utility motives. If this was the case, it may also be that these same residents are more supportive of clean energy infrastructure than subsidies for utility-sponsored EE programs due to a lack of trust in the energy utility organization. Furthermore, there are differences in awareness based on how messages were framed among residents who were mis-informed about EE programs and those who were unaware. Mis-informed residents, or those who said that there were no energy utility EE programs, were significantly less likely to have positive perceptions about utility motives for offering EE programs.

Residents who participated in EE program offerings were significantly more likely to view utility motives positively, to be more supportive of government subsidies for EE, and to be more supportive of utility use of clean energy than those who did not participate. Residents who participated were supportive of GHG reduction from reduced consumption (i.e., EE) as well as infrastructure (i.e., clean energy). These findings provide support to the notion that residents who are engaged in efficiency have a clearer understanding of the entire system because they are participating than those who are only aware of EE program offerings. As expected, residents who participated in EE programs viewed energy utility motives more positively than those who did not or who were unsure. Also, significant differences emerged for gender, political affiliation, and income consistent with previous studies (e.g., Atkamis, 2011; Brouhle & Khanna, 2012; Coffey & Joseph, 2013 Craig & Allen, 2014).

The findings in Chapter 3 are generally supportive of the logic behind the Ajzen's theory of planned behavior (TPB; 1991), while not causal. Those who were aware of EE programs were more likely to participate in EE programs and also more likely to positively perceive utility motives. However, mis-informed residents were more supportive of government subsidies for EE programs than those who were aware, and unaware residents were more likely to support utility use of clean energy than those who were aware. While attitudes are not explicitly examined in Chapter 3, it may be that the manner in which EE programs are communicated is not clearly related to the negative consequences of electricity use, including GHG emissions from energy utility organizations. Residents who participated in EE programs, however, were more likely to support GHG reduction in terms of EE subsidies and clean energy use. The observed gap between awareness and participation in terms of support for energy utility organization GHG reduction is consistent with previous gaps between awareness and pro-conservation behaviors (e.g., Allcott & Greenstone, 2013; Craig & Allen, 2014). Residents who participated in EE in their homes were more supportive of measures that benefit the broader environmental system.

Chapter 3 also highlighted that incentives and actual savings from EE offerings used by residents did not have a significant impact on reducing electricity consumption. Allcott and Mullainathan (2010) noted that non-economic driven behavioral approaches to efficiency including social norms can drive pro-conservation behaviors. Simple actions such as asking for a commitment from residents has the potential to increase residential engagement with EE programs. As noted in previous studies, the use of norms to promote pro-environmental behaviors is difficult because of the private nature of electricity use in the home (e.g., Clement et al., 2014; Lo et al., 2015). Chapter 3 used both environmental and social science methods to

address the knowledge gap about the influence of climatic and EE programs on electricity consumption.

Chapter 4 explored how experiential learning can be utilized in a school setting to increase student environmental literacy and reduce electricity consumption in the school and in student homes. In this chapter, an experiential, curriculum-based learning intervention was used to increase knowledge and build student empowerment to overcome the gap between knowledge and action to engage in pro-conservation behaviors. As predicted, results demonstrated that experiential learning in the school improved environmental literacy. Students vastly improved from pre- test to post-test when asked about the unit used to measure electricity and what uses the most electricity in the home. As stated in Chapter 4, while environmental learning in the school is not a new concept, it remains an exception rather than the rule due in part to the voluntary nature of environmental-focused curriculum and lack of funding. Sovacool (2009) suggested the use of environmental and energy curriculum to disperse efficiency throughout communities. This study positioned the curriculum-based intervention under the umbrella of literacy as opposed to science or technology, providing more opportunities to fit within common core standards for elementary students.

Percentage change in electricity consumption in student homes and in the school facility was used to assess Hypothesis 2 and 3 in Chapter 4. For both the school and the home, in the control month electricity consumption increased. Following the deployment of the behavioral intervention, the school facility saved upwards of 30% in electricity when controlling for HDD, and over 15% was saved in student homes. The findings support previous studies where behavioral programs engaged students to save electricity in school facilities (Bulman & Ehrendreich, 2010; Cross et al., 2010). The study extended the literature by quantifiably

demonstrating electricity savings in student homes. Combined, findings suggest that children can understand the complex electricity system, including what electricity is, how it is consumed in school and at home, and how to engage in pro-conservation actions to decreases consumption.

Chapter 4 provided valuable insights into previous studies related to the TPB and electricity consumption, where the desired pro-conservation behavior is reduced consumption. While not explicitly discussed in Chapter 4, the application of the TPB in practice and in future research is present. The intervention in the school allowed students to experientially learn about and engage in EE behaviors in the school, and students were asked to repeat exercises in the home. Students gained the knowledge to act (i.e., behavioral control) and had a positive experience with the interventions (i.e., positive attitude). Additionally, in the school and at home, students became a normative influence on adults. Even when utility companies provide households with direct and real-time feedback about electricity usage as part of EE programs, it is unlikely the normative effort of such information will be as strong as students actively engaging adults. Teachers were held accountable in classrooms, maintenance and facilities staff were held accountable throughout the school facility, and parents were held accountable in student homes. Mixed results and non-significant results in previous pro-conservation TPB studies (e.g., Clement et al., 2014; Lo et al., 2014) suggest the need for normative mechanisms to improve electricity reduction intentions and behaviors. Chapter 4 provided a case study with a method to engage occupants in the organizational facility (i.e., the school) in a manner that also diffuses pro-conservation throughout the community.

5.1.2 Implications

Energy utility organizations have historically been the most salient producer of CO₂ emissions (Heede, 2014). Consequently, energy utility organizations have also consistently spent

more on EE efforts than any other stakeholder in the US (Gilleo et al., 2014). EE efforts have the potential as a cost-effective method to reduce residential electricity demand and the associated GHG emissions from energy utility organization generation. As posited in Chapter 4, a holistic approach that integrates awareness and learning with EE DSM and demand reduction efforts holds the most promise to transformationally influence pro-conservation behaviors. When behavioral, communicative mechanisms are not integrated into residential EE initiatives, however, a rebound effect that offsets electricity savings is common, and in many cases, resulted in increased electricity consumption (Delmas et al., 2013; Greening et al., 2000). When considering the most effective mechanisms to deploy EE efforts, transformational change and persistent energy reduction is most likely achieved through a combination of behavioral and economic nudges (Allcott & Mullainathan, 2010; Herring, 2006; Sovacool, 2009; Thaler & Sunstein, 2008). For policy makers and regulators responsible for EE programs and GHG reduction targets, it is important that the effectiveness of EE program offerings is taken into consideration and energy utility organizations are held accountable.

Chapters 2 and 3 demonstrated that while funds continue to be allocated to efficiency programs (Gilleo et al., 2014), the effectiveness of EE offerings in the current form are questionable across the US. Residential electricity consumption continues to increase, and this increase is strongly related to GHG emissions. As Povacool (2009) noted, a mixed strategy that is not solely reliant on economic incentives or subsidies for old technologies, and that incorporates learning for future and current generations is needed. Chapter 4 demonstrated quantifiable savings in the school facility and in student homes, yet spending from energy utility organizations on schools remains low. Furthermore, EE offerings historically have not engaged

occupants to maximize electricity savings in the facility or to achieve electricity savings in student homes.

Environmentally legitimate behaviors are those that are proper, appropriate, and desirable (Bansal & Clelland, 2004). Accountability and credibility are integral for environmental legitimacy to occur, particularly for energy utility organizations that have been tasked with championing a public-focused environmental issue such as deployment of EE programs (Alrazi et al., 2015). As noted throughout the study, for-profit businesses such as IOUs will pursue profit-seeking behavior driven by market forces absent outside intervention (Sioshansi, 2013; Weimer & Vining, 2011). Across the US and in the focal Southeastern state this appears to be the case. Billions of dollars are allocated each year towards utility-championed EE programs (Gilleo et al., 2014). However, as demonstrated in Chapter 2 and 3, residential-focused offerings are often ineffective. The relatively low incentive levels for residences (Asensio & Delmas, 2015) in addition to the exclusionary nature of EE to low-income residents (Craig, 2016; MacGill et al., 2013; Weiner & Vining, 2011) is also prohibitive to EE program effectiveness. These findings are consistent with previous studies that have shown mixed or negative results as a result of poor communication and a rebound effect (e.g., Delmas et al., 2013; Gillingham et al., 2013; Greening et al., 2000). This body of this study provided multiple methods to control for climatic interactions with electricity consumption that can be utilized to quantitatively assess successfulness of interventions targeting electricity conservation, including EE offerings and learning interventions.

In a few Northwestern states including Oregon and Washington, EE program offerings were significantly related to a decrease in residential electricity consumption. In each of these states, EE spending was high early in the study period, and decreased along with consumption.

This was despite a significant increase in CDDs. In this region, a non-profit organization was tasked with the deployment of utility EE programs (Cropp et al., 2014). While not causal, it may be when profit objectives are removed, the integration of transformative efforts that integrate increased awareness and deployment of EE measures is likely to increase savings levels and persistence. In other states, however, it was common for EE spending to respond to increased demand rather than to pro-actively mitigate demand. Spending may have included incentives for DSM measures such as efficient light bulbs, improved the building envelope, or enhanced efficiency of air conditioning units. Response and mitigation are both needed. For energy utility organizations and regulators alike who are tasked with improving the effectiveness of EE program offerings, it would be helpful to use the states in the Northwest that were able to utilize EE programs to effectively lower residential electricity consumption, such as Oregon, as a case study.

The results of this study provide insights into differences in individuals and messaging tactics to increase resident engagement in EE and support for GHG reducing policy. For instance, individuals who are aware of EE programs are significantly more likely participate in EE programs. Likewise, individuals who participate in EE programs are more likely to support GHG reduction by utilities than those who do not participate. As mentioned in the introduction, awareness precedes TPB variables. These findings suggest the importance of successfully using messages to increase participation in EE by individuals and support for energy utility organizations to reduce GHG emissions. Previous research has suggested that messages related to not harming the environment, saving energy, and promoting personnel health have all been successful at influencing engagement in EE (e.g., Asensio & Delmas, 2015; Craig & Allen,

2014). In Chapter 4, the use of experiential learning was also linked to increased knowledge about EE and electricity usage, as well as pro-conservation in residences.

For energy utility organizations pursing EE in schools or looking to expand experiential learning to other residents, this study provides a model that can increase environmental literacy and electricity savings that is quantifiably proven using a relatively low-cost behavioral approach. The results were consistent with previous studies, and show just how impactful a behavioral approach that includes organizational members can be to the facility and to the surrounding community. There are opportunities for funding agencies focused on environmental literacy and behavior change, such as NOAA or the EPA, to utilize the case study in Chapter 4 as a model to enhance current and future environmental educational efforts as well. Funding from energy utility organizations, funding agencies, or both, will only increase the likelihood of widespread deployment of proven learning interventions throughout schools and other organizations.

5.1.3 Future research

Much work remains to be done to understand the complex electricity system, and how natural and social sciences can be integrated to inform GHG reducing mitigation strategies. For future researchers, it may be necessary to work in coordination with energy utility organizations to gain access to the resolution of data needed to adequately model future relationships between generation, consumption, and climate. It may also be necessary for federal agencies, including the United States Department of Energy, to re-examine reporting parameters for utilities in the absence of private-public cooperation. Household-level data as well as higher frequency data would allow for extremely high resolution analysis of climatic interactions down to a specific

address. Where smart thermostats in place in households (e.g., Asensio & Delmas, 2015), this is becoming increasingly feasible.

Specific to electricity consuming residents, future research should integrate climatic data with social science data to better understand the short- and long-term impacts of climatic variability and extreme events on resident knowledge, attitudes, perceptions, behaviors, and support for policy. For instance, the use of drought indices could be integrated with interval-level social science data to perform a host of different analyses to understand the climatic impact on an individual's attitudes and use behaviors. Pro-conservation behavioral mitigation strategies can be customized down to the household level based on findings from such research. The use of a national sample matched with climatic data is desirable. Also, actual behaviors should be observed in the household relative to electricity consumption in addition to self-reported behavior similar to the methodology used by Asensio and Delmas (2015). Climatic variables can also be integrated with TPB variables to determine the impact of actual pro-conservation behaviors relative to intentions, self-reported behavior, attitudes, perceptions, and support for policy. Path modeling and other advanced causal statistical techniques should be used in this analysis.

Climate change is a global problem, thus, the research of climatological interaction with electricity systems should be replicated globally. Additional variables are needed to increase the predictability of future models and to increase the variability explained by historical models. For instance, McFarland et al. (2015) noted that future models for electricity demand do not adequately account for outside factors such as efficiency and population. Furthermore, extreme weather events such as extreme hot days, extreme cold days, and extreme precipitation events should be integrated into future models. EE was factored into historical models in this study, and

should be included in future models. In addition to using other input variables, additional outcome variables should be studied as well. For instance, it would be useful to examine the impact of conservation efforts on water systems taking into account climatic variability and consumption. With drought predicted in the Southeast US in particular (Ingram et al., 2013), future models that take into account both electric and water systems are needed.

Higher resolution generation and consumption data is needed for future research. Real-time, daily, and weekly data were not available for consumption, generation, or EE for this study. The highest level of data available was monthly data reported by energy utility organizations, and in Chapter 3 the only electricity data available was annual. It may be that joint research projects between academic institutions and energy utility organizations may be necessary to explore the climatic interaction with electricity consumption, generation, and efficiency savings to produce data at a high enough resolution to adequately inform future models.

Researchers should also expand experiential learning nationally and globally in schools, and continue to quantifiably track outcomes related to conservation. By adding a qualitative, ethnographic component to studies where researchers observe interactions in the home and in the school between students and adults, the influence of normative pressure or nudges can better be understood. Chapter 4 supports previous research that curriculum-based, experiential learning interventions in schools are successful at improving knowledge and electricity savings. Core standard requirements and timing constraints in the classroom make it a necessity that curriculum materials are applicable to all schools and seamlessly replicable. To accomplish a national trial that expands best practices across the US, interventions that are easy to install and replicable are needed. It may be necessary for funding agencies who focus on environmental literacy, such as the NOAA or the EPA, to participate to expand such efforts. The development

of a user interface that students and teachers can use to engage with experiential learning and track behaviors would be a great stride. An easy to use interface would also make it more feasible to measure the persistence of pro-conservation behaviors, including electricity reduction in schools and in homes, over time. The applicability of experiential learning in other non-educational organizations is also needed. Previous studies demonstrated the impact of organizational initiatives in the workplace (e.g., Allen, 2016), however, the impact to pro-conservation efforts when employees go home is not well known. Future research considerations are discussed in more detail above in Chapters 2 – 4.

5.2 Conclusion

This study provides a theoretical and methodological basis by which the influence of climatic interaction on electricity consumption can be examined while taking into account proconservation behaviors, including EE programs and student learning. In Chapters 2 – 4 significant positive relationships emerged where climatic indicators were significantly related to residential electricity consumption. Combined, findings from all chapters demonstrated the interconnectedness of climatic trends and complex energy systems. Looking forward, mitigation strategies including efficiency and policy are needed to address anthropogenic forced climate change and extreme weather events associated with GHG emissions.

EE programs have shown promise in a few regions throughout the US. For instance, electricity consumption was negatively related to EE program savings in a few Northwest states and negatively related to indirect EE spending in the focal Southeast state. Progressive policy and behavior change are at the forefront in these two study areas, respectively. Policy in the Northwest allocated funding up-front instead of in response to electricity demand like most states in the US. In the Southeast state, non-incentive costs associated with marketing efforts and

personnel were the influential factor; incentives for upgrades or technology were not significantly related to electricity consumption. Taking all results from the study into account, it suggests that proactively addressing electricity consumption with holistic, behaviorally integrated EE efforts can counteract the positive relationship commonly associated with both population increase and increased CDDs. In order to achieve long-term electricity reduction goals, EE programs and government policies need to move beyond response strategies.

The value of knowledge, learning, and awareness about energy conservation and GHG reduction cannot be understated. This is true inside and outside the walls of the organization. In terms of policy, residents who were aware about EE programs were more likely to participate, and those who participated were more likely than those who did not to support GHG reducing policies. In states and / or regions throughout the US where EE programs are not effectively reducing electricity consumption and are not offsetting the negative impacts of increasing CDDs, policy may be the most viable option for GHG reduction. The use of effective messaging campaigns to increase knowledge and awareness is necessary. In the face of resistance from energy utility organizations to adopt clean energy infrastructure, it may also be necessary for outside entities (e.g., nonprofits, governmental) to intervene to improve resident conservation behaviors and improve attitudes, support, and / or perceptions about pro-environmental policy. In order to truly mitigate GHG emissions to reduce risks associated with climate change, action from all stakeholders discussed in the study is needed, whether through individual behavior, internal energy mix decisions by energy utility organizations, or governmental intervention.

There are approximately 90,000 school organizations in the US. The number of school entities dwarfs even the largest for-profit organizations in the US in terms of number and square footage. In a school setting, students who were able to learn through experience at the school's

facility were able to take what they learned out in the community to exponentially expand the positive impact of conservation efforts. The school facility itself also experienced substantial electricity savings, a finding consistent with previous studies. The materials and the methods to improve learning and actionable electricity use conservation behaviors in schools have already been created. As with other large social movements to reduce effects of harmful behaviors, schools and students can play a major role in the reduction of GHG emissions and transformation towards a pro-conservation minded society that is not dependent on fossil fuels.

Combined, this interdisciplinary study adds to multiple literatures, providing insights informed by theory and best practice for academics, practitioners, policy makers, and regulators. These stakeholders are tasked with designing, deploying, and tracking GHG mitigation strategies to combat climate change. People are the primary cause of climate change, and people around the world are all impacted by increased climatic variability and extreme weather events. As evidenced by the continued increase in electricity consumption among residents in this study, more holistic and quantifiably viable alternatives – including efficiency, policy, and energy infrastructure management – are needed to reduce the associated GHG emissions that are driving climate change. There is a need to move beyond a micro-only or macro-only perspective when examining the interaction between climate, organizations, and society. By adhering to a systems-based approach that incorporates all points along the macro-micro continuum, the ability of decision makers to understand climatological and societal interactions will be enhanced, and interventions that reduce anthropogenic caused GHG emissions can be vastly improved.

5.3 References

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