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A Human Side Of The Smart Grid: Behavior-Based Energy Efficiency From Renters Using Real-Time Feedback And Competitive Performance-Based Incentives

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A HUMAN SIDE OF THE SMART GRID: BEHAVIOR-BASED ENERGY EFFICIENCY FROM RENTERS USING REAL-TIME FEEDBACK AND COMPETITIVE PERFORMANCE-BASED INCENTIVES

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Abstract

Our energy system is rapidly transforming, partially due to advances in internet and communications technologies that leverage an unprecedented amount of data. Industry proponents of the so-called "smart grid" suggest these technologies facilitate deeper engagement with end-users of energy (utility customers) that can in turn drive behavior-based changes and accelerate a renewable energy transition. While there has been progress in understanding how these technologies change consumer behavior using, for example, real-time feedback, it's unclear how specific segments (e.g., renters) respond to these interventions; it's also unclear why feedback is, or is not, producing changes in energy consumption. The literature suggests that behavioral strategies (e.g. information feedback, competitions, incentives) coupled with technology may present a way for utilities and efficiency programs to create savings—expanding opportunities for those often underserved by traditional approaches, such as renters—yet this coupling is not well understood, neither broadly (for all end users) nor specifically (for renters).

This dissertation builds upon that literature and explores a human side of the smart grid, using a field experiment in renter households to test the interacting effects of real-time energy feedback and a novel form of financial incentive, referred to here as a competitive performance-based incentive. The experiment had two phases: phase one tested the feedback against a control group; phase two tested feedback, the incentive, and a combined treatment, against a control group. Results of these interventions were measured with pre- and post-treatment surveys as well as observed electricity consumption data from each household's smart meter.

The results of this experiment are described in three papers. Paper one examines the interventions' individual and combined effectiveness at motivating renters to reduce or shift timing of electricity consumption. Feedback alone produced a significant savings effect in phase one. In phase two, the effect of the feedback wore off; the incentive alone had no significant effect; and the group that received feedback and the incentive experienced a doubling of savings relative to the effect of feedback alone, as observed in phase one. Paper two uses pre- and post-intervention survey data to examine how individual perceptions of energy change as a result of the interventions. Perception of large energy-using appliances changed the most in households that received feedback, suggesting that better information may lead to more effective behavior changes. Paper three leverages the results of the first two components to evaluate the policy implications and impacts on demand side management for utilities, efficiency programs, and the potential for behavior-based energy efficiency programs. Advocates of the smart grid must recognize the technology alone cannot produce savings without better engagement of end-users. Utility rate designers must carefully consider how time-based rates alone may over-burden those without the enabling technology to understand the impact of their energy choices.

Citations

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In honor of my grandfathers,
Norman Wertheimer and Sam Fredman,
who both passed away while I worked on this document.
I'll remember you, always.
Thanks for everything.

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1 Introduction

1.1 A Personal Story

Before beginning my PhD work at UVM in 2013, I was a sustainability program coordinator on a large university campus for almost five years; specifically, my role emphasized outreach and education. As part of a team tasked to reduce the carbon footprint associated with the university's operations, we strategically engaged all levels of the institution to create and act on a climate action plan that would also foster a culture of sustainability on and off campus. After completing a greenhouse gas inventory, it became clear the main source of emissions from campus operations were tied to the energy consumption of campus buildings and their operations. To address this, we worked closely with administrative units of the campus that dealt with design and operations of both new and old buildings including capital planning, architecture & design, engineering controls, and waste management.

Over time, following a campus policy to follow LEED specifications (a prominent national green building certification standard) on all major projects, capital planning led to construction of new greener buildings (and renovations of existing buildings) that included advanced building automation systems. These systems gave facilities managers the ability to monitor and control the comfort of the building while also managing energy consumption. From the other side of the campus, facilities managers in their offices could see the overall operations of a new building in real time (for example, one could see temperature and carbon dioxide levels fluctuate in each room such that a manager would know that a class was no longer in session). In addition to this monitoring capacity, buildings with these systems also had automated controls to conserve energy, such as motion sensors that could power down lights when no one was in the room or exterior light sensors that would automatically raise or lower shades based on available daylight. The saying “what gets measured gets managed” was in full effect here; the campus leadership could see with precise data how better monitoring and control systems could lead to operational efficiencies and savings on energy costs, but this type of system came with great expense and investment in advanced, technical systems. This solution–greener buildings engineered for efficiency with precise and automated management–had potential to deliver on its promise of measurable energy savings, but did so without any real engagement with the buildings' occupants and was done at great financial cost to the institution (that, ideally, penciled out for the bottom line while improving the university's "green" bona fides).

Our small, scrappy, sustainability office–perhaps by lack of budget or a desire to work from a more systemic, grassroots perspective (or both)–took a different approach to energy savings and efficiency that emphasized personal behavior changes. As part of our ongoing waste management and recycling operations, we had developed close relationships with building service workers (BSWs) charged with emptying trash and recycling bins across the campus. We also had relationships with many other campus departments through regularly planned outreach events like a green festival or used office supply exchange. With a small investment covering printing costs, we printed small stickers that designed to fit over light switch plates or along the edges of computer monitors and remind individuals to power down after leaving a desk or room. These stickers were handed out at all our outreach events and we handed them out at our recycling trainings with BSWs, who would then put them on light switches in the facilities they managed (they would also get training to turn off lights when leaving certain rooms at the end of their shift). Eventually, we saw these stickers in most spaces around campus, and at later outreach events we would get requests for more stickers and often were told by staff that they took the stickers home to put up in their kids' rooms. We saw this as a strong signal that the stickers were being well-received and, anecdotally, perceived that behaviors were being changed; with these stickers going home, we felt there was potential for "spillover effects" in which other sustainability behaviors might be happening beyond the campus boundaries. Unfortunately, this low-cost, grassroots approach would prove difficult to measure and tease apart from other ongoing initiatives on campus (like the previously-mentioned engineering-focused green building efforts as well as, for example, ongoing lighting retrofits or retrocommissioning projects targeting existing HVAC systems).

It is this experience working on issues relating to energy conservation and behavior change in the context of climate action–and this dichotomy between less expensive, human-centric, hard-to-measure strategies and technology-centric, data-rich, more expensive projects – that motivates my dissertation. My interests, previous educational experiences (studying psychology and urban planning), and work experiences (before and during my time as an IGERT fellow) among institutions developing climate solutions have inspired me to explore a personal interest in the relationship between people and technology; in this document, I hope the reader sees the opportunity for my dissertation to contribute to a deeper understanding of this tension while exploring the evolving utility-customer relationship and its implications for the future, especially to help sustainability practitioners (or simply those focused on energy efficiency) better quantify the benefits of behavior-based energy interventions.

1.2 Purpose

This dissertation will explore the potential benefits of new emerging technologies available to residential energy consumers, specifically renters, made possible by the so-called "smart grid" (SG) taking shape through a loosely coordinated effort to modernize the electric grid. Another goal is to discuss how these technologies and behavior-based interventions can facilitate more meaningful interactions between and among stakeholders in a modern energy system–specifically between customers, utilities, and efficiency program managers–that could accelerate a renewable energy transition. Through a field experiment coordinated by a research team made of up members of local institutions (a utility, city, and university) and a technology provider, the dissertation will use experimental data measuring changes in energy literacy (perceptions and knowledge) and electricity consumption in rented residential properties. The dissertation research outputs will attempt to characterize any energy savings resulting from behavior changes in these properties associated with the two primary experimental interventions of real-time information feedback (using In-Home Displays or IHDs, a type of energy monitor) and competitive performance-based financial incentives (see the methods section for more details). The dissertation will also attempt to quantify and evaluate any potential benefits garnered through residential energy efficiency measures and conservation using these behavioral interventions and consider their policy implications.

The central thesis of the dissertation is that while new technologies aligned with the smart grid create opportunities to engage customers to create efficiencies that facilitate a renewable energy transition, it will require a better understanding of the human dimensions of these technologies, including how individuals interact with it, to truly realize this transition. This dissertation will test the following hypotheses: that technology (in this case, real-time feedback through in-home displays) can improve energy literacy and induce energy conservation; that behavioral economics can be used to nudge consumers and help technology be more effective; and that when aligned properly, behavioral nudges augmented by technology can produce cost-effective, verifiable savings that may be used in energy efficiency programs. Explained with more detail in the following sections, the goal of the research will be to add to the body of literature by weaving together large, high-resolution energy datasets and appropriate mixed methods analysis techniques informed by the social sciences. A recent statement from Frederiks, et al. is quite relevant:

> In particular, questions remain over the utility, scalability and cost-effectiveness of the various [behavioral] interventions intended to influence energy consumers, as well as the contexts, contingencies and boundary conditions that either constrain or facilitate the impact of such interventions. Because human [behavior] varies across time and situations, and within and between individuals, there are limits to the [generalizability] of research findings. Future research should therefore focus more on understanding not only what predicts consumers' [behavior]–and importantly, what predicts changes in such [behavior] across time and place–but also when, where, how, why and for whom these effects occur

(Frederiks, Stenner, & Hobman, 2015, p. 1391).

1.3 Context & Motivation

The following introductory sections describe the underlying context motivating this research and why the research represents an important contribution. Simply put, while similar work has been done to examine the influence of feedback on energy consumption (Abrahamse, Steg, Vlek, & Rothengatter, 2007; Allcott & Rogers, 2014; Attari, Gowrisankaran, Simpson, & Marx, 2014; Brewer et al., n.d.; Cappers et al., 2013a; Ehrhardt-Martinez, Donnelly, & Laitner, 2010; Foster & Mazur-Stommen, 2012; Karlin et al., 2015b; Petersen, Shunturov, Janda, Platt, & Weinberger, 2007; Robinson, 2007; Vine, Buys, & Morris, 2013), opportunities to improve upon this work exist and are detailed in the following sections of this document. First, enriched data collected by a smart grid (in this case, Advanced Meter Infrastructure data from smart meters) provide an opportunity to use larger and higher-resolution customer energy consumption data; this dissertation will take advantage of these large datasets, which have not been available to much of the previous body of work. Second, for many reasons (including sparse consumption data collection and experimental constraints), previous work has often lacked the combination of rigorous research design and reporting on methods and statistics, leaving the true benefits of certain behavior-based interventions unclear; this dissertation will attempt to address methodological gaps that ensure future reproducibility and offer more clear insights. Third, and perhaps most importantly, whether out of convenience or intent most experimental research in the residential energy sector of this type has focused on a general residential population; this dissertation specifically seeks to better understand the rental housing population. This group has been growing steadily since the turn of the century for a variety of reasons (e.g., changing patterns of employment and work mobility, rising housing costs, or previous debt making homeownership unviable or undesirable) and presents a potential threat to standard efficiency programs, primarily from split-incentive problems (discussed further in section 1.4.3).

Taken together these themes of a utility landscape undergoing disruption, a need to better quantify and understand the human element in energy, and a shifting housing population threatening standard efficiency practices present an opportunity for the proposed research to contribute to an underdeveloped body of literature that supports necessary advances in the energy field. As Karen Ehrhardt-Martinez states:

> understanding the human dimensions of energy offers the promise of generating valuable insights about our energy culture, historical and future shifts in our everyday energy practices, sources of variation in our energy-use patterns, and effective mechanisms for transforming how people, organizations and societies use energy. These insights can empower people and organizations to become the source of innovative, broad-based energy and climate solutions that could dramatically amplify and catalyze our ability to reduce energy consumption and carbon emissions and transform our energy culture (Armstrong et al., 2016, p. 6).

1.4 Comprehensive Literature Review

1.4.1 A Changing Energy Landscape

1.4.1.1 Utilities, the Smart Grid, and Smart Meters

A modern, flexible power grid has become necessary for modern life: The current grid is aging and in need of upgrade and repair; consumers demand for electricity is growing and they also want more control of and choice in their energy supply; the environmental and economic realities of fossil fuels are becoming more clear requiring expansion of distributed energy resources (DER); and the cost to produce electricity from renewable sources continues to decline. Since development of the modern internet in the early 1990s, internet and communications technologies (ICT) have been at the center of disruption and innovation in nearly every sector of society. As computing power increased while shrinking in physical size, data storage capacity and density has expanded while becoming less expensive per unit of storage. These advances, among others, allowed for the emergence of wireless, distributed sensor networks and supporting infrastructure (which also shrunk in size and price over time), fostering an "Internet of Things" (IoT) industry that facilitates measurement, monitoring, and controls of potentially every physical object, whether by human, human-to-computer, or a machine-to-machine (M2M) relationships. The electric utility sector, responsible for providing safe and secure electricity that is the cornerstone of modern civilization, is broadly experiencing this explosion of digital technologies and IoT as the so-called "Smart Grid" (or "smart grid") (SG) and its associated "enabling technologies."

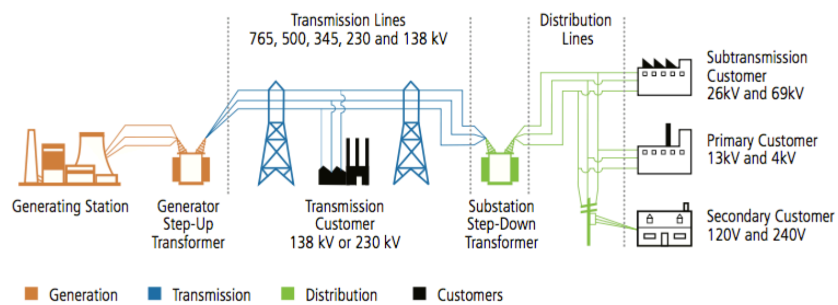

Figure 1: Conceptual model of basic electric power system (US Department of Energy, 2015a).

The smart grid may mean different things depending on the audience (Stephens, Wilson, & Peterson, 2015). The smart grid, at its simplest definition, is a traditional power system embedded with ICT in nearly every aspect. As Figure 1 shows, a traditional electric power system is made up of infrastructure elements comprising a series of centralized generators, a transmission system, a distribution system, and the ultimate end users (i.e., consumers, customers) of energy (Union of Concerned Scientists, 2015). It was originally designed for power to flow in one way, from the generators out along transmission and distribution networks towards customers. As the power system developed in the early 20$^{\text{th}}$ century, this made physical and economic sense–it was most efficient and cost-effective to build large, centralized power plants rather than smaller generating resources for every community, especially when the primary fuel supply was coal or oil with high transportation costs (not to mention environmental impacts). Over time, as electrification became more widespread and demand grew, local and regional grids became intertwined via high-voltage transmission lines that evolved into the current national grid infrastructure we have today, considered to be the largest interconnected machine in the world (see Figure 2 for a map of the current transmission system) (US Department of Energy, 2008). This system, along with much of the country's infrastructure, however, is showing its age and needs to be upgraded for modern needs–an estimated $673 billion in investments by 2020 (Halsey III, 2012).

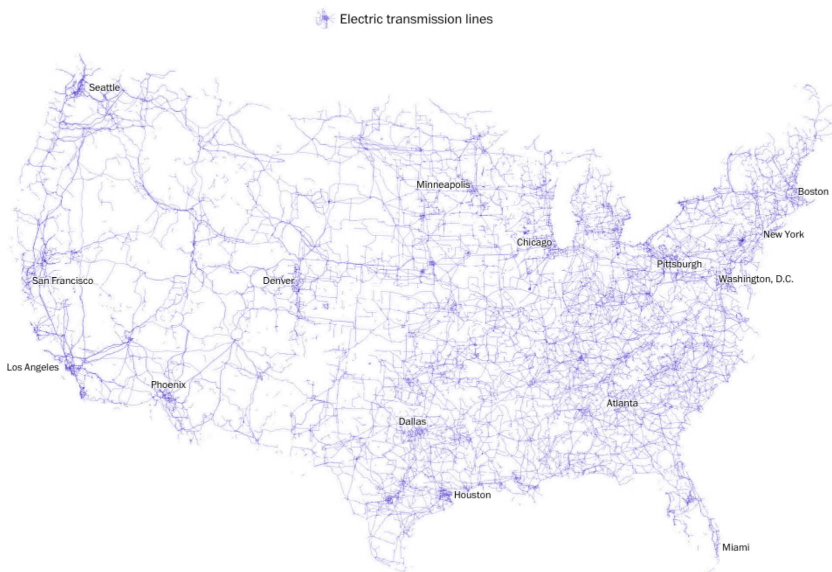

Figure 2: Over 160,000 miles of electric transmission lines in the United States, connecting about 7,700 power plants and 3,300 utilities (Meko, 2016).

In a smart grid, rather than the one-way flow of electricity described above, electricity may flow bi-directionally between all components and is managed with a new communications network intertwining all elements, allowing for safe integration of smaller, distributed energy resources (DER) from wind, water, and solar (WWS). The National Institute of Standards & Technology (NIST), in laying out a framework for understanding and synchronizing the vast scope of the smart grid and its development projects, describe it as "a complex system of systems, serving the diverse needs of many stakeholders," including service providers who develop systems or devices for the smart grid, residential, industrial and business customers, utilities of varying scale and scope, and regulators (Greer et al., 2014). The NIST vision of the smart grid, depicted in Figure 3, considers it a networked system of seven domains–Markets, Operations, Service Providers, Customers, and the traditional grid elements of Generation, Transmission, and Distribution–each with their own stakeholders, needs, and components. Nearly every element–every switch, circuit, generator, meter, transformer–will be able to communicate its status, send and receive signals, and be automated to act in certain conditions or be controlled remotely in real-time. This paradigm shift from a centralized system to one that is distributed and networked suggests the smart grid "has the potential to transform the relationship between energy consumers, energy producers and energy distributors"(Koliba, Brune, Berman, Zia, & Moreau, 2013). There is a need to better understand how this transformation affects these relationships, especially the diverse customers who ultimately demand what the smart grid should be able to support: safe, reliable, clean electricity.

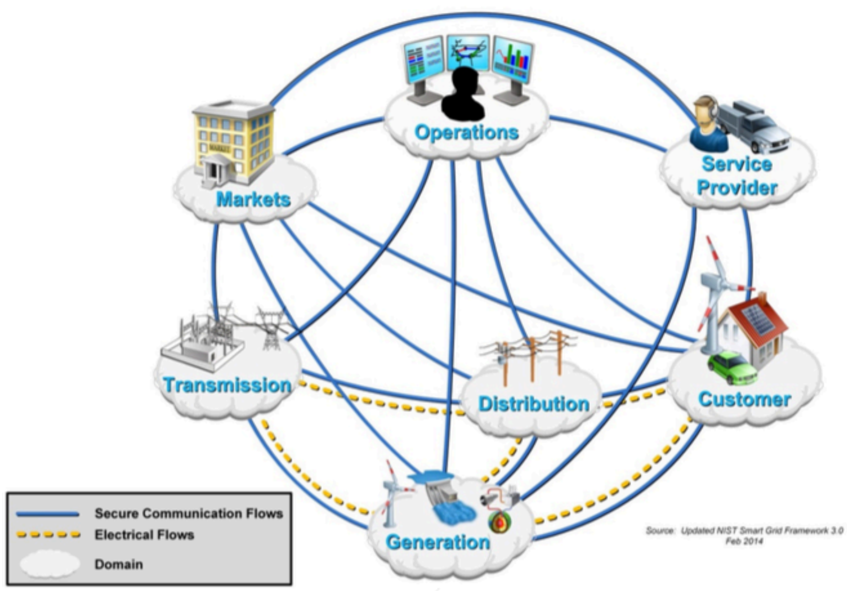

Figure 3: Conceptual model of the smart grid (Greer et al., 2014).

The evolution from grid to smart grid has taken shape over decades, in fits and starts emphasizing different sets of enabling technologies, and is not yet complete. To date, one of the most significant national investments in SG infrastructure was ultimately a product of the economic collapse triggered by the housing crisis. In 2007, the United States Congress passed the Energy Independence and Security Act (EISA) which identified a need for a national smart grid and called for federal matching of investments in this infrastructure (Rahall, 2007). Shortly after the Great Recession, the U.S. Department of Energy (DOE) received $4.5 billion in stimulus funding as part of the American Recovery and Reinvestment Act (ARRA) of 2009. With this ARRA funding, DOE could jump-start grid modernization programs authorized by the EISA, the largest component being the Smart Grid Investment Grants (SGIG). The $3.4 billion of these ARRA funds went into SGIG, when combined with utility-funded investments, ultimately contributed to a total $8 billion in national electricity system investments. Of the 99 SGIG-funded programs, a majority of them implemented Advanced Metering Infrastructure, or AMI (U.S. Department of Energy, 2016). AMI is a suite of smart grid enabling technologies that include smart meters, two-way communications networks, and a hosted meter data management system (MDMS), an upgrade from previous Automated Meter Reading (AMR) infrastructure that delivered meter-level consumption data wirelessly to a utility (EPRI, 2007). AMI enables a bi-directional communications relationship between grid operators and the myriad elements of customer domain (see Figure 4), opening potential applications to deliver real-time information to the customer about electric costs, grid status, or potentially send commands to smart appliances in the home. This dissertation focuses on smart grid technologies related to residential customers in this domain: meters and home gateways.

There is no one-size-fits-all method to modernizing the electric grid, as there are many different business models and regulatory environments across the United States; in fact, states have shown to be ideal testbeds for electric utility innovation, and Vermont is one of the first states to coordinate state-wide deployment of their smart grid(US Department of Energy, 2015a). As of late 2015, the Edison Institute indicates there are approximately 65 million smart meters deployed around the United States (covering approximately 50% of all households), with that number expected to reach 90 million by 2020 (Cooper, 2016; Mooney, 2015). Figure 5 maps out the status of US smart meter deployments by state.

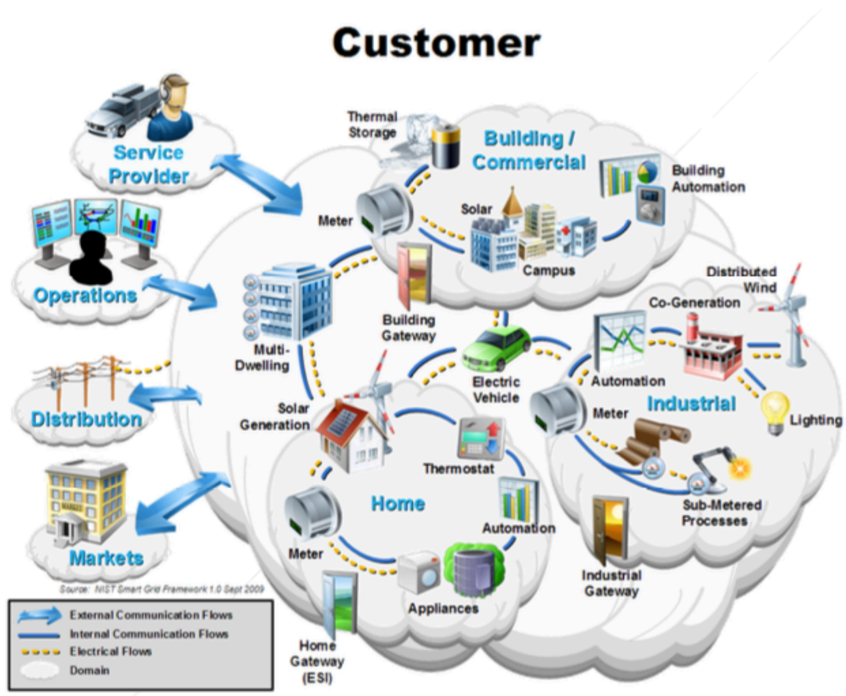

Figure 4: Customer domain detailed conceptual model (Greer et al., 2014).

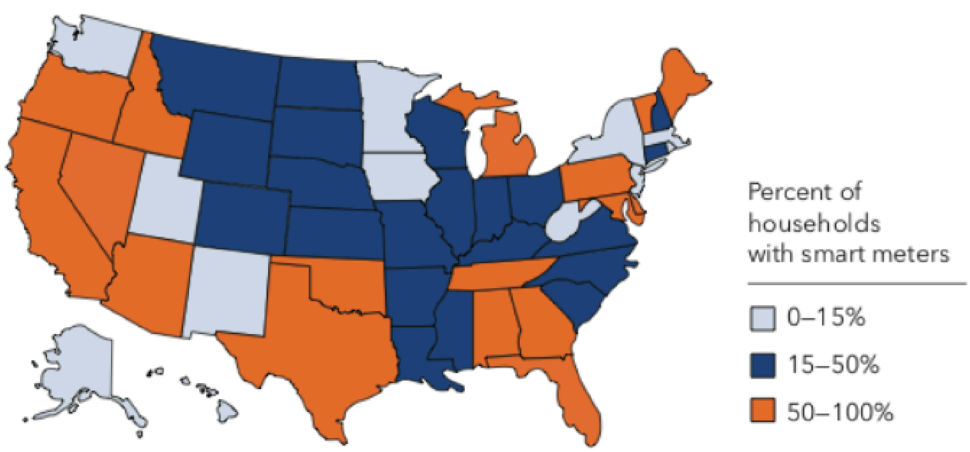

Figure 5: Edison Institute map of smart meter deployments by state as of 2015. Automated Meter Reading (AMR) meters are not included(Cooper, 2016).

A state-level view is helpful, but when considering customers, we should think about who interacts with electric customers most–their utilities. Figure 6 depicts the distribution of utilities serving residential customers (by total residential meters along the x-axis) and penetration of advanced meters (both AMI and AMR, along the y-axis) based on Energy Information Administration data available from 2014. Nearly 70% of all electric utilities serving residential customers have deployed either AMR or AMI in more than 90% of their service area, but many still have not completed their deployments. The median number of meters in all utility service areas is approximately 7,000 and the average meter count is approximately 63,000; this average value is skewed by the relatively fewer number of investor-owned utilities that serve larger territories and customers. For context, the residential customer base of the Burlington Electric Department (BED) is just less than 20,000 meters and over 90% of its residential meters use AMI, making it an ideal test case to explore how utilities are using smart meters to engage customers. This happens to put BED in a "sweet spot" as one of the most advanced municipal utilities in terms of the smart grid and advanced meters; BED is also representative of many utilities when considering the size of their customer base. As of October 2016, according to the Edison Institute, more than 16 million advanced meters had been installed in municipal and cooperative utility service areas (Cooper, 2016).

For context of this dissertation, AMI (and AMR) provides the infrastructure that enables real-time feedback of energy consumption data through Home Area Networks (HANs) and In-Home Displays (IHDs). While third-party providers can allow customers to buy their own IHDs and create HANs, it is important to view this through the lens of a utility because utilities can use these resources to engage their customers, help them obtain personal energy savings, and create conditions that benefit grid stability as more DERs become integral to grid operations. These technologies will also allow consumers and utilities to better understand their own energy consumption patterns and improve potential demand side management (DSM) programs based on consumer behavior.

1.4.1.2 Demand Side Management & the Smart Grid

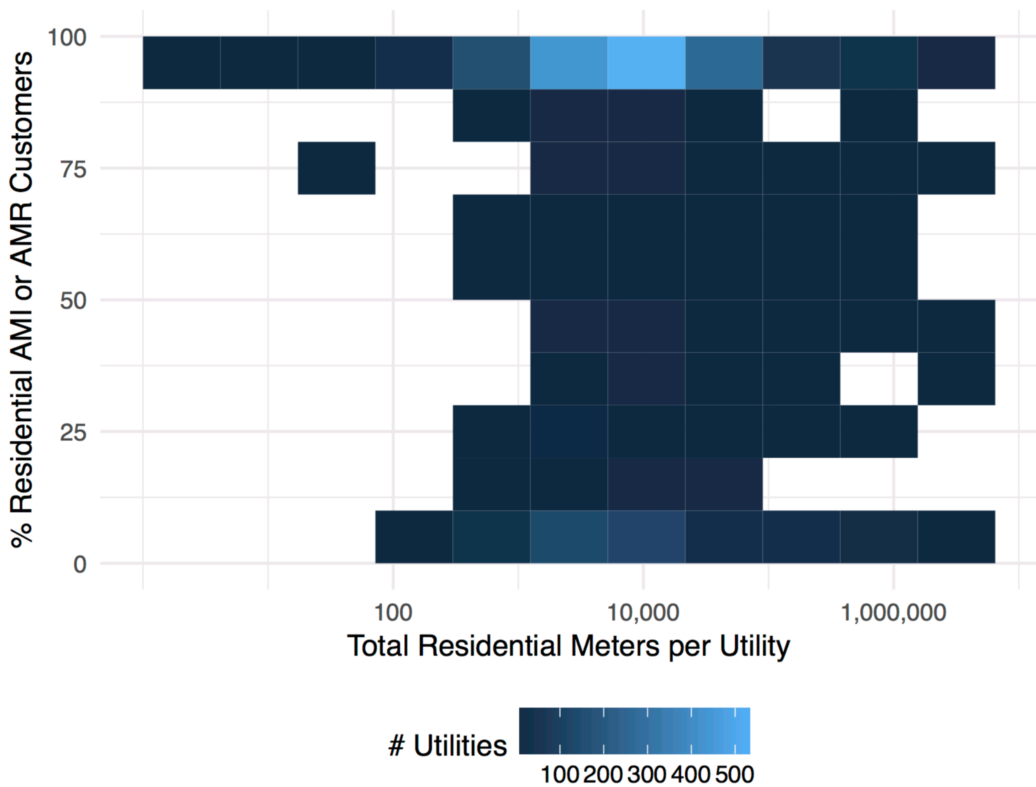

Figure 6: AMI and AMR penetration in residential utility territories. Data source: EIA (2016)

Electricity is unique in that it is not easily and economically stored; supply must meet demand at any given time or the power system is at risk of failure. As demand for electricity grows, grid operators have developed complex markets and systems for making sure this demand it is met with adequate supply-side resources by going through long-term integrated resource planning (IRP) processes to bring supply resources online. Historically electric utilities have focused on building new supply to meet demand, which is capital-intensive, and over time grid operators have developed methods to influence when and how much electricity is demanded; if managed properly, it is possible to avoid building costlier supply-side resources. Over the past few decades, these resources for DSM have grown; these approaches fall into two primary approaches–Energy Efficiency (EE) and Demand Response (DR)(Behrangrad, 2015). These approaches to DSM, explained below, are changing with the grid itself and new approaches continue to emerge. As the smart grid continues to evolve, there will be new challenges and opportunities that allow program designers and utilities to drive efficiency and engage customers in new ways that adapt to changing supply constraints. A driving force will continue to be the reality that energy efficiency is very cost-effective. Paraphrasing American Council on an Energy Efficiency Economy (ACEEE) President Steve Nadel, it turns out the least costly kilowatt-hour to supply is the one never used (ACEEE, 2014).

1.4.1.3 Energy Efficiency

Energy Efficiency (EE) programs, which reduce the energy required for existing products and services by replacing them with new products that consume less energy, are widely regarded as an effective strategy to decrease demand for energy and, subsequently, reduce greenhouse gas emissions (Geller, Harrington, Rosenfeld, Tanishima, & Unander, 2006). Energy efficiency is also considered the fastest, least expensive, and most environmentally friendly way to deal with the threats relating to resource depletion and climate change (Ottinger, 2006). In 2014, EE expenditures in the United States was $7 billion (Gilleo et al., 2015). These programs typically work by creating purchasing incentives (usually discounts or rebates) to end-users or upstream stakeholders (like a retailer or product manufacturer) that accelerate adoption of a more energy-efficient technology. For example, even though they had a shorter lifetime and consumed more energy than existing compact fluorescent lightbulbs (CFLs) or light-emitting diodes (LEDs), incandescent light bulbs used to dominate the marketplace for lighting because they were less expensive per bulb and had a preferable lighting quality. National and state EE programs worked to bring down the costs of CFLs and LEDs to customers, stimulate R&D to improve quality, and develop regulations to improve the efficiency of incandescent bulbs (effectively making them obsolete). The market for lighting has been transformed by EE programs, and it is now typical to find CFLs and LEDs at comparable prices to a traditional incandescent (because the market is shifting and these incentives still exist). EE programs are not just for light bulbs: programs exist for many different appliances and work to increase efficiency in many markets, including refrigeration and clothes washers/dryers, home construction (like windows and insulation), and vehicle efficiency (like tax rebates for efficient vehicles). Until recently, these programs have focused on shifting product markets, improving industrial and commercial processes, and encouraging customers to choose more efficient products. With precise consumer-level smart meter data, EE programs are also beginning to incorporate consumer behavior, whether in the marketing strategies of traditional widget-based efficiency programs or by developing methods to account for measurable behavior changes due to program components. These smart meter data, combined with customer demographics and advanced analytics, have the potential to improve how efficiency opportunities are presented to customers. It seems that these data-driven consumer behavior-based programs are a step towards a blend of traditional efficiency programs with the other side of DSM, Demand Response.

1.4.1.4 Demand Response

The Department of Energy (DOE) defines Demand Response as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"; in essence, this is targeted and incentivized curtailment (US Department of Energy, 2006). Originally conceived as a means of managing emergency spikes in demand that threatened grid stability due to supply constraints, DR programs are generally categorized two ways: incentive-based programs and time-based rates (Demartini, 2013). DR programs differ from EE programs in that they do not generally require expenditures for new equipment or appliances that consume less energy; DR programs are usually set up by energy providers or vendors who, under predetermined conditions, will pay consumers of energy to reduce their demand for a short period of time (Rochlin, 2009). With the automation capacity of the smart grid, theoretically it's possible for consumers to opt into programs that allow grid operators or third-party aggregators to manage appliances during peak periods (for example, air conditioners could be powered down remotely). There is potential to leverage consumer behavior for demand response, most commonly expressed as time-varying electricity rates.

1.4.1.5 Measurement & Verification using the Smart Grid

Approximately 35 states have programs that focus on electric efficiency and are funded by utilities through ratepayer efficiency fees (Barbose, Goldman, & Schlegel, 2009). To justify using ratepayer funds for an efficiency program, or to prove that a program can deliver on promised energy savings and contribute to resource planning in energy markets, it must undergo a rigorous screening process to verify predicted energy savings (Todd, Stuart, Schiller, & Goldman, 2012; Vermont Department of Public Service, 2016). To support the energy efficiency market and foster standard practices, DOE developed standard protocols to conduct measurement and verification (M&V) for ratepayer-funded efficiency programs (US Department of Energy, 2015b). The process of M&V helps add precision and accountability to efficiency programs, making them competitive with (and less costly than) fixed capital investments.

M&V is becoming more complicated as traditional energy efficiency programs successfully change the market. Consider the earlier example of lightbulb efficiency programs. As the market becomes saturated with more efficient products and, in this case, incandescent bulbs are replaced with less frequency as they're phased out, efficiency programs will soon no longer be able to rely on these savings claims (York et al., 2015). Efficiency opportunities have not dried up; it's just that they have now become more complex and diverse, requiring new and creative solutions (York et al., 2015). In their report, "New Horizons for Energy Efficiency," York, et al. describe this evolving state of "Efficiency 2.0" that will require new measures that depend on technological innovation, systems solutions, and behavior change (2015). They go on to investigate how diverse approaches, one of which include real-time feedback and incentives, potentially will contribute to an estimated 15-31% energy savings over the next 15 years. They conclude with a set of broad recommendations to utilities and efficiency program managers to capture these diverse, complex energy savings opportunities, many of which justify this dissertation. Of their concluding recommendations in the report, the following findings are relevant and related to this dissertation:

- **Research markets** to better understand the needs, preferences, and behavior of customers to customize programs and target specific segments. *This dissertation will focus on the rental housing market.*

- **Complement and catalyze** new markets by watching for new opportunities and develop programs to support them. *This dissertation will examine the potential for a novel behavior-based programs, linked to the smart grid and internet of things (IoT), in residential rental properties.*

- **Support demonstrations and research/development** of new and emerging technologies. *This dissertation is based on a demonstration/R&D project supported by a municipal utility and the state of Vermont.*

- **Broaden program options** to include appropriate new technologies and work with program partners, ensuring customers are educated about the benefits and new solutions have the best chance to succeed. *There will be significant co-learning in partnership with the utility to* *discover how best to utilize customer-facing aspects of the smart grid.*

- **Integrate and target behavior change opportunities** by influencing the way customers understand and interact with devices, systems, and entire buildings. *The emphasis of the dissertation is on how customers interact with and use new technologies, and how their perceptions and behaviors may be changed by such technologies.*

- **Run pilot programs** to explore new methods, models, and technologies and improve cost-effectiveness. *This dissertation attempts to analyze different aspects of a utility pilot program.*

It is with this changing nature of efficiency programs in mind that the dissertation will attempt to add to the body of knowledge informing strategies to find energy efficiency (and conservation) opportunities from new technologies and behavior change. Feedback has been shown to be a promising tool to drive reductions in energy consumption either through curtailment practices or efficiency investments (Ehrhardt-Martinez et al., 2010; Foster & Mazur-Stommen, 2012; Karlin et al., 2015b). However, much of the literature evaluating the role of feedback contains inconsistencies and lack of clarity in the reporting of experimental design, data collection, analysis method, and results making it hard to draw strong conclusions quantifying the benefits of feedback on energy consumption (Karlin et al., 2015a).

1.4.2 The Need for Behavior-Based Energy Efficiency

Without economic sacrifice or harm to well-being, household behavior changes resulting in decreased energy use can be an efficient and effective means to cut carbon emissions; up to $300 billion in gross energy savings (about 25% potential savings) through 2020 are possible with currently available technology (Dietz, Gardner, Gilligan, Stern, & Vandenbergh, 2009; Gardner & Stern, 2008). Despite this potential, they are not widely adopted and behavioral science can support policy makers in finding solutions; although a variety of these actions are technically and economically viable, widespread adoption is lagging and policy makers are increasingly looking to psychologists for guidance (Karlin et al., 2014; Wilson & Dowlatabadi, 2007). Furthermore, in the domain of energy-related research, there is a substantial lack of social science relative to the physical sciences in this area despite the notion that "problem-focused research activities [that center] on both physical and social processes, include diverse actors, and mix qualitative and quantitative methods have a better chance of achieving analytic excellence and social impact" (Sovacool, 2014a, p. 530). In a recent examination of over 4400 articles in prominent energy journals, comprising nearly 10,000 authors, 13-17% of the articles focused on energy efficiency and approximately 23% of the authors had interdisciplinary affiliations, suggesting a lack of transdisciplinary research; behavioral topics were not listed in the top five topical or technical foci in these articles (Sovacool, 2014b). This suggests the outputs of the dissertation will constitute a valuable contribution by blending elements of social science into the study of energy.

As discussed in Section 1.4.1.5, there are established standards and practices for evaluating energy efficiency that include efficiency measure design, data collection requirements, and evaluation methods (US Department of Energy, 2015b). Due to the complexity and variability in the last 30 years of investigations into the energy savings potential of behavior change, there are now established protocols for understanding the energy impacts of behavior-based (BB) efficiency programs, such as randomized control trials (RCTs), which are rooted in previous research (Stewart & Todd, 2015). These BB programs typically include interventions that involve outreach, education, competition, rewards, feedback, and benchmarking (Todd et al., 2012). Thorough reviews and meta-analyses have been conducted of existing utility-run BB program evaluations across 101 service territories (Mazur-Stommen & Farley, 2013) and experimental evidence of these intervention methods (Darby, 2006; Ehrhardt-Martinez et al., 2010; Fischer, 2008; Karlin et al., 2015b; Vine et al., 2013; Vine & Jones, 2016), suggesting that BB programs can cost-effectively deliver potential average energy savings of 4-12%, but when real-time feedback at the household level was used, savings averaged closer to 9%(York et al., 2015). Table 1 describes some of the types of feedback and their potential savings impacts.

Table 1: Meta-analysis findings from Ehrhardt-Martinez, et al.(2010).

Type of Feedback	# Studies	% Studies	Min Savings	Max Savings	Avg Savings	Median Savings
Enhanced Billing	11	19%	1.2%	10.0%	5.2%	5.5%
Estimated Feedback	3	5%	5.1%	8.5%	6.8%	6.8%
Daily/Weekly	15	26%	3.7%	21.0%	11.0%	10.8%
Real Time (Household)	23	39%	-5.5%	32.0%	8.6%	6.9%
Real Time (Appliance)	5	11%	9.0%	18.0%	13.7%	14.0%

Some of these programs found negative savings (i.e., energy use went up) or savings well above these ranges, but were excluded because of inconsistent study design issues or the studies done in homes that were already highly efficient (Robinson, 2007). Despite the deep history of research involving energy feedback there are, however, gaps in the literature. While there is a strong signal over the past 30 years that these programs and interventions may be effective, there is still a need to use more “rigorously executed experimental designs to systematically test the impact of a variety of social science-based program elements in real-time feedback systems [within] households”(Armstrong et al., 2016). As Dougherty & de Grift put it, “to date, the great majority of evaluative research has focused on the question ‘Do behavioral programs save energy?’ and to a lesser extent on the question ‘How do behavior programs work to save energy?’ ”(2016).

Bruekers and Mourik (2013) describe energy-related behaviors broadly as intentional or habitual, but further explain them on a spectrum spanning persistence, consciousness, and frequency (see Figure 7). While not directly stating this in their goals, traditional efficiency programs have historically focused on one-shot, infrequent actions that occur on the left side of this spectrum, such as motivating purchase of the most efficiency appliance or home. The true uncharted territory in behavior-based energy efficiency is related to the more frequent, harder-to-change unconscious habits and routines. More research is needed to understand which mechanisms cause behaviors and their associated energy consumption to change; this dissertation will attempt to do this.

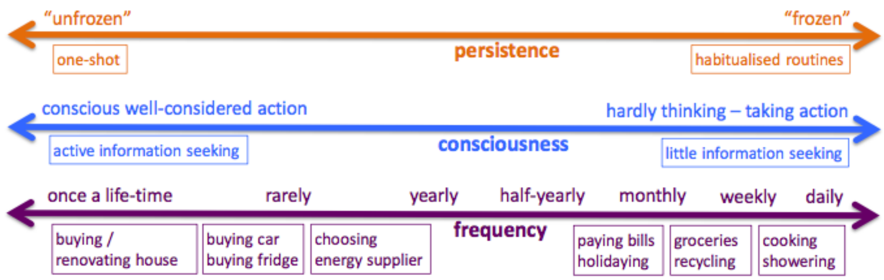

Figure 7: Behavior spectrum from Breukers & Mourik (2013). Efficiency programs commonly target behaviors on the left side with rebates, incentives, and education materials, but newer behavioral efficiency programs (and this dissertation) attempt to influence behaviors and habits on the right side.

1.4.3 Residential Trends & Impact on Efficiency Programs: A Looming Threat?

The housing market is changing and may have an impact on residential energy efficiency savings potential. Efforts currently exist to encourage greater energy efficiency in multifamily residential buildings and have varying degrees of success (Philbrick et al., 2014b; Pivo, 2014). For example, states like Vermont and Illinois offer instant rebate programs to subsidize the cost of efficiency measures (such as light bulbs or home energy audits), reducing barriers to access by residents (Robinson, 2014). This does, however, require an investment in time and/or money on the part of the home's occupants to reach the goal of reduced energy consumption. The occupant, whether a renter or an owner, may have varying levels of motivation and laziness may override any rational financial gain as was the case with one interviewed homeowner (Morse, 2014). There are also differences in how homeowners and renters consume energy; for example, owner-occupied units consume more total energy than renter-occupied units, but renter-occupied units consume more energy per square foot (Carliner, 2013). This would suggest that while homeowners gravitate towards larger homes, renters lack the capacity or ability to be more efficient. Quite simply: renters consume energy differently than homeowners.

While it has long been considered part of the "American Dream" to own a home and perhaps some

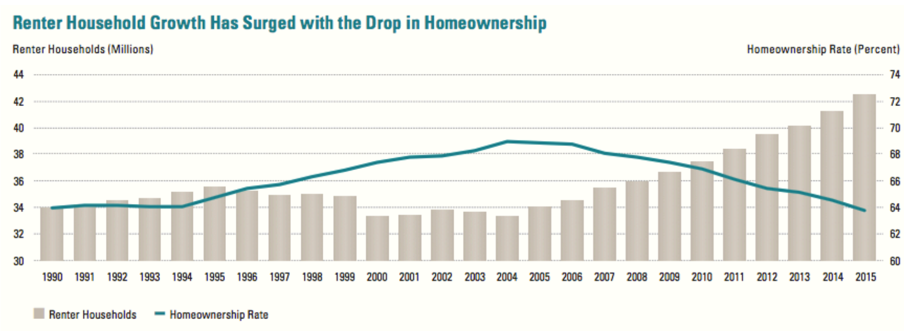

Figure 8: Changing patterns of US homeownership, 1990-2015, from the Harvard Joint Center for Housing Studies (2015). US Homeownership rates have had historic declines over the past decade and rental households have surged.

land, where and how people live in the United States is changing. The world population recently became over 50% urbanized and, as of 2010, 80.7% of the U.S. population live in urban areas. The preference for homeownership over renting is changing as well; Figure 8 shows how homeownership populations have changed since 1990. Hart Research Associates conducted a quantitative and qualitative study of renters and homeowners for the MacArthur Foundation. Among those surveyed, there was still a predominantly strong desire to own a home but most respondents believed buying had become less appealing and renting had become more appealing. The study goes on to explain that this shift is tied to the economy (a result of the housing crisis) and lifestyle changes, and both current renters and homeowners believed that that renters can be as successful as homeowners. Despite the shift in housing preferences, the study found that across all social and political demographics there was a strong desire for safe, affordable, and stable housing, in any form (Hart Research Associates, 2013). A study from Harvard's Joint Center for Housing Studies indicated that 37 percent of American households were renters in 2015, up from 31 percent in 2004, marking this decade as the largest period of growth in renters ever recorded (2015). Both the Hart and JCHS studies indicate that the population of renters is growing against that of homeowners, and given the policy realities around carbon emissions there is a need to address energy efficiency in the residential sector. However, energy policies–and, in relation, housing policy–does not adequately meet the needs of renters (and this is exacerbated in the low-income renter population, who disproportionately feel the expenses of energy relative to wealthier renters).

In this context, affordable and stable energy costs in the home would be desirable as well; it would make housing–rental housing in particular–more affordable (Philbrick et al., 2014a). Thus, increasing the energy efficiency of homes would make energy costs more reliable, if not lower. Gillingham and Palmer describe a so-called "energy efficiency gap" in which energy efficient products are adopted at a slower than optimal rate, and explain how market failures and behavioral factors contribute to this gap in all types of consumers (2014). One of these failures is known as a "split-incentive" or "principal-agent problem" and it occurs in many instances besides energy efficiency. When this problem occurs the interests of two parties do not align, and these competing goals and motivations result in market failures. Considering energy efficiency and split-incentive gaps in rental properties, a landlord may be responsible for the appliances or equipment in the property while the tenant is responsible for paying for the electricity used by them; the landlord has no incentive to upgrade to more efficient appliances because they would not see any cost savings, yet the tenant may never recoup the cost savings of a more efficient appliance during their tenure, so the appliance is not purchased (Carliner, 2013). It is for reasons like this, and the lack of existing policy interventions, that rental properties are often avoided in efficiency retrofit efforts (Robinson, 2014). Avoiding these properties just as their population swells in the housing market suggests a real risk to the viability of current energy efficiency practices that depend on residents to invest in energy efficiency because of long-term savings.

A recommended solution to this "split-incentive" problem, however, is increasing access to information. Many sources, including a current renter (Stewart, 2014), utility operators (Buckley, Green, & Burns, 2014), an efficiency service operator (Robinson, 2014), and sampled literature (Carliner, 2013; Gillingham & Palmer, 2014) have indicated better information would be desirable and would lead to better decision making. This may refer to rating and labeling programs–such as EnergyStar–as well as novel efforts to require information about utility costs being made publicly available and benchmarked (Cox, Brown, & Sun, 2013). Carliner notes that an effort to bring benchmarking and disclosure of energy expenses in rental housing is underway, and this may help renters choose where to live (2013). This has been met with some difficulty, however, and as an example in Chicago, politicians play up the drama by referring to benchmarking as "public shaming" (Wernau, 2013) and is not the purview of this dissertation. However, AMI (and the Smart Grid) can play a role by providing residential utility customers access to their consumption information in near real-time (Koliba et al., 2013). For instance, one renter explained that having access to more precise, accurate information would help monitor and adjust behavior at home in the interest of reducing consumption; this renter also indicated that if utility costs were too high it would motivate her to find another place to live (Stewart, 2014). Utility employees expressed strong interest in a more effective means of deploying the benefits of AMI to the renter population because it would help influence the behavior of a significant portion of their service territory that has been previously difficult to access (Buckley et al., 2014). It's still an open question of whether renters respond to energy feedback universally the same way that homeowners have been shown to respond. Recent research suggests that "vulnerable populations" (e.g., elderly, low-income, or chronically ill households) may respond in subtlety different ways compared to average households, and more research into specific populations is needed (Cappers et al., 2016).

1.4.4 Universities & Sustainability

Just as utilities must evolve to handle the shifting supplies of electricity, they must also adapt to shifting characteristics in their customers. As of 2015, millennials (generally, people born between the early 1980s and 2000s) make up more than one quarter of the US population at 83.1 million (US Census Bureau, 2015). They constitute a class of energy consumer that expects utilities to provide a seamless digital experience to manage their energy, provide choices and options in energy products, and would be more than twice as likely to sign up for solar panels than baby boomers (Tweed, 2016). Many millennials are college-aged and older, a time when renting is most common; this group is also delaying marriage, perhaps extending the period in which they would be likely to rent (Joint Center for Housing Studies of Harvard University, 2015). This population (35 and younger) is also the largest renter age group in the country–over 20 million households, as depicted in Figure 9.

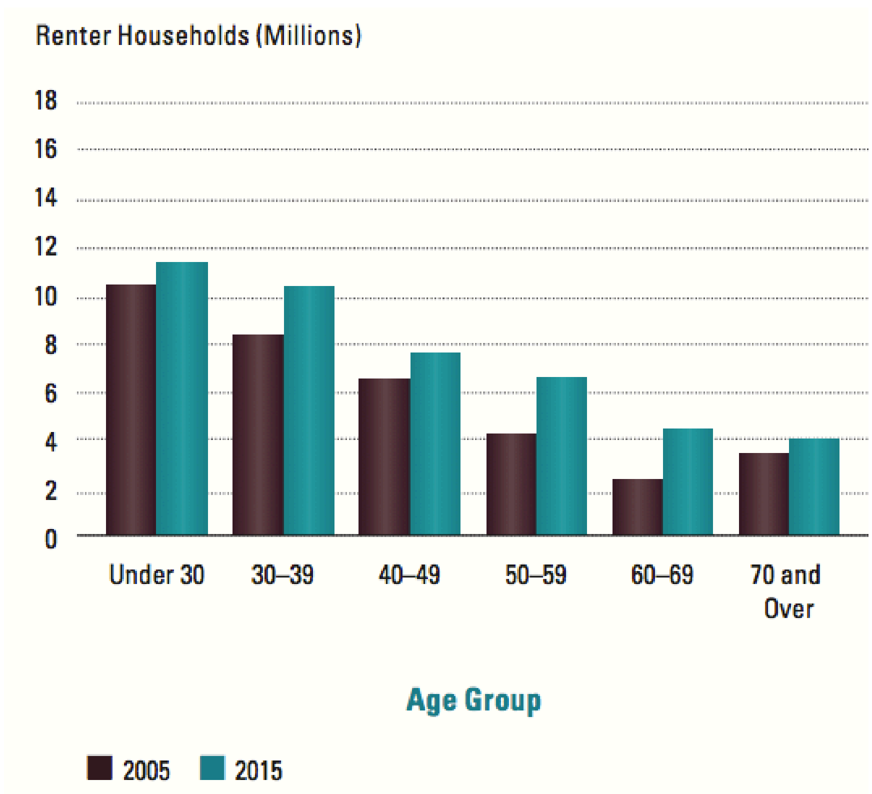

Figure 9: Rental household growth by age group, from Harvard's JCHS (Joint Center for Housing Studies of Harvard University, 2015). While decade-over-decade growth in renters comes from all age groups, especially residents in their 50s and 60s, younger adults make up the largest segment of renter households.

Current college students–millennials–living off-campus are not only an available population for a university research project, but also represent a market segment utilities need to better understand. In our field experiment, students who live off-campus have recently made the transition away from the relative protection of campus life (perhaps, excluding some older graduate and medical students) and are, in most cases, just learning how to manage personal expenses like rent and utilities. This presents a unique opportunity not only to understand how this population responds to new technology, but also to try to create pro-environmental habits that may be locked in through adulthood.

1.5 Methods

The following sections describe the methods taken to conduct and carry out the field experiment.

1.5.1 Experimental Background & Justification

For the U.S. Department of Energy's Consumer Behavior Studies (CBS), a part of the Smart Grid Investment Grants, researchers at the Lawrence Berkeley National Lab (LBNL) created guidelines and protocols for designing and evaluating various behavioral interventions including feedback (in-home displays) and incentives (time-of-use rates) (Cappers et al., 2013b). To measure and evaluate the significance of a these interventions, the "Gold Standard" experimental method is the Randomized Controlled Trial (RCT) in which eligible research subjects of are randomly assigned to either a treatment group or control group (Todd et al., 2012). Randomization ensures that the treated and controlled populations are comparable and any measured differences in the two groups can be reasonably attributed to the intervention. The field experiment deployed for this dissertation and proposed chapters attempt to follow these guidelines and evaluation practices as well as suggestions described by the IEA Demand Side Management Energy Efficiency Technology Collaboration Program (DSM TCP) recommending survey data collection of behavioral dimensions before and after an RCT intervention (International Energy Agency (IEA), 2015). Along with these recommendations, and the most recent meta-analyses of experimental evidence testing behavioral energy information strategies (Delmas, Fischlein, & Asensio, 2013; Karlin et al., 2015b) (both published since 2013), some clear methodological fault lines emerge where future work can improve upon. Synthesizing previous work (Cappers et al., 2013b; Delmas et al., 2013; International Energy Agency (IEA), 2015; Karlin et al., 2015b; Todd et al., 2012), studies examining feedback should, when possible, include:

- A dedicated control group, where subjects in this group are monitored the same as treated groups
- Controls for weather (i.e. heating degree days or hours)

- Controls for demographics and household-level characteristics
- Randomization (treatment or encouragement to treat)
- Factorial designs isolating treatment variation between conditions
- When necessary, greater attention to the physical design and presentation of feedback displays
- Repeated and persistent data collection, including baseline data
- Comprehensive presentation of methodology and results (to enable greater replication and interpretation of findings)

All these recommendations were considered in the field experiment design. What follows is a description of the methods used in the field experiment deployed for the dissertation.

1.5.2 Field Experiment Overview

To address the dissertation questions, a field experiment was conducted to observe renters' responses to both real-time feedback of electricity consumption and incentives to adjust the timing and magnitude of electricity consumption in the household. Real-time feedback was defined as information delivered instantly via an enabling technology – an in-home display (IHD) – that connected wirelessly to the research subjects' home electric meter. Incentives were defined as the offer of financial rewards in exchange for an energy consumer's desirable response; the offer was delivered via email. See later sections for specific details of the feedback mechanisms and incentives delivered as part of the field experiment.

The study was principally funded by the University of Vermont (UVM) Clean Energy Fund (CEF), the UVM Smart Grid IGERT, and the Burlington Electric Department (BED) with administrative support from the UVM Gund Institute for Ecological Economics. As a municipally-owned utility, BED's capacity to support the experiment was partially funded by the American Public Power Association's Demonstration of Energy & Efficiency Developments (DEED) grant (American Public Power Association, 2016) and had administrative assistance from the City of Burlington's Community & Economic Development Office (CEDO). The study has been referred to amongst stakeholders broadly as the "UVM Energy Study" or the "UVM Off-campus Energy Study" (OES). OES primary goals were to: (1) acquire a library of IHDs for repeated use within the university community; (2) develop the utility's long-term capacity to support IHDs and other smart grid-compatible enabling technologies; (3) evaluate the potential uses of IHDs in the residential rental market; (4) support innovative research relating to the smart grid; and (5) create an opportunity to engage university students about their personal energy use. This dissertation primarily addresses goals 4 and 5.

In a broader sense, the implementation of this project represents a complex collaboration - initiated and facilitated by graduate students with advisory support from faculty - between the university, the city, and the utility to progress towards the shared vision of a sustainable community powered by clean and renewable energy using constrained human and financial resources. The study's features – including the treatment groups chosen and the technology provider used – were selected based on consultation with university funders and the utility during the planning stages to understand the goals of these organizations and any potential policy outcomes. The utility wanted to test new technology and its applicability in the rental market while not over-burdening the utility's IT department responsible for mission-critical day-to-day systems operations; they also wanted to explore novel rate designs and methods of customer engagement, despite limitations presented below. The university was interested in developing new ways to engage students on energy topics and potentially establish a resource (a library of IHDs) that survived past the experiment timeline.

1.5.3 Field Experiment Design

In this experiment, subjects screened for eligibility were randomly selected to be offered one of four treatments, making up a 2x2 factorial design: (1) energy information feedback; (2) incentives; (3) combination of information feedback and incentives; or (4) control (no offer of treatment). See Figure 10 for a visual representation with randomized treatment population counts that resulted from this process. Subjects in groups that received the information treatment were loaned an IHD that was retrieved after the study period, which ran from September 2015 to May 2016.

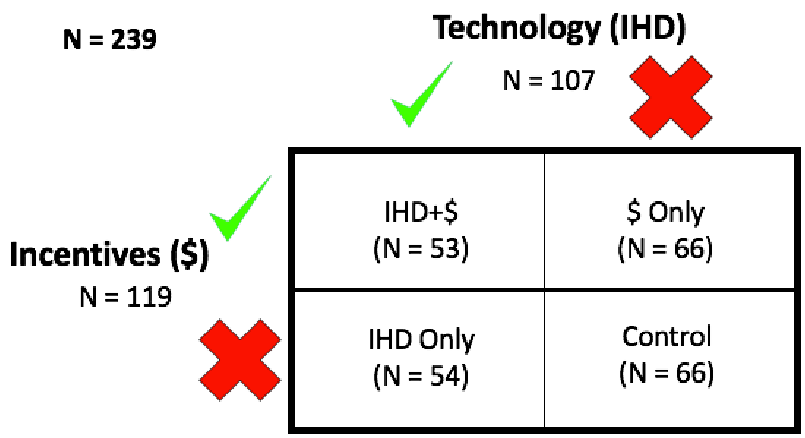

Figure 10: Factorial research design with treatment populations

1.5.3.1 Research Subject Recruitment

Subjects were recruited early in the Fall 2015 semester using email invitations, reminders, and public outreach requesting completion of a screening survey (described in Appendix A: Survey Instruments). Potential subjects were drawn from a population of active undergraduate, graduate, medical, and continuing education students (N = 7738) confirmed by the university to be living in off-campus campus housing not managed by the university. The screening survey included questions that recorded housing characteristics and respondent tenure in the household as well as customer details to facilitate matching households with utility data (e.g., address, utility ratepayer name, which were later removed from the dataset for privacy concerns) and to screen for eligibility for the any treatment in the study (internet access, smartphone/tablet ownership, and interest in using a device to display real-time information). The screening survey also included questions that recorded subjects' current attitudes, beliefs and future intentions about home energy use and conservation behaviors, based on recommendations from previous experimental and theoretical work (Abrahamse & Steg, 2011; Allcott & Mullainathan, 2010; Attari, DeKay, Davidson, & Bruine de Bruin, 2010; Karlin et al., 2015a, 2015b; Todd et al., 2012) to be described in later sections. Based on these survey responses, if for some reason the study was executed unsuccessfully, deploying this screening survey first would obtain sufficient data to analyze the behavioral antecedents of energy use and associated AMI data in this population (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Abrahamse et al., 2007; Karlin, Ford, & Frantz, 2016; Stephenson et al., 2010).

An attempt was made to maximize study participation by drawing from behavioral insights. Building on a previous experiment that tested methods to increase survey participation, respondents were incentivized to participate using a regret lottery with social pressure (Todd, 2010). Subjects were invited to participate in the survey and informed of the following conditions: (1) The respondent's name has already been added to a prize drawing for $100 and winners will be chosen at random; (2) if their name is drawn and they have not completed the survey, there would be no winner; (3) if their name is drawn and they did complete the survey, they would win $100. Drawing from evidence that social pressure can motivate participation in charitable giving (DellaVigna, List, & Malmendier, 2009) and voter turnout (Gerber, Green, & Larimer, 2008), the survey invitation informed potential subjects that the respondent would have an option to choose a friend who would also win $100 should the respondent be chosen in the prize drawing. In addition to this social pressure, subjects were informed that to maximize their personal chances of winning, the respondent should ask others to complete the survey and request they be listed as the designated recipient of the "friend prize." The survey was open to responses for approximately eight weeks and had a 10% response rate (N = 772).

These responses were screened to reveal potential subjects who had wireless internet access at home, a mobile device (iOS or Android smartphone or tablet), and name/address combination that could be matched by the utility to have an active account in the utility service area (N = 239). The internet and mobile device requirement was to ensure every participant could use the full suite of resources provided by the IHDs if they chose to do so. There were additional respondents who met all criteria except their name was not listed on their home's utility account (i.e., respondent's roommate was the ratepayer); the utility had stringent privacy rules that, even when the respondent indicated on the screening form that the ratepayer had granted permission to participate, their energy consumption data could not be transferred without additional contact and confirmation with the ratepayer. To offset a selection bias (Heckman, 1979) where subjects may have only been interested in experiencing this new technology, subjects selected to receive an IHD were offered $50 at the end of the study period. This substantial financial compensation was considered enough to attract subjects who would otherwise be disinterested in using an IHD. As one participant stated upon receiving their device, "this was the easiest $50 I ever made; I just have to go home and plug this thing in?"

To ensure protection of subjects' privacy, design of the research program and screening survey went through appropriate IRB approval. All subjects had informed consent regarding how they might be expected to participate and how their personal data would be used and protected both during the experiment and after it ended. Any subject who completed the screening survey received information at the beginning, during, and after the survey form submission process explaining how personal data would be used. Subjects who received the information feedback treatment completed and signed a consent form that explained the process and expectations for receiving and using the technology, how they would be compensated, and what to expect when the experiment was completed.

1.5.3.2 Feedback Treatment

The feedback treatment group received an in-home display (IHD) made by CEIVA Energy (CEIVA Energy, 2016). CEIVA was selected as the vendor through a deliberative process between the utility and the researchers, ultimately due to their software and hardware offerings, price, and the assessment of expected shelf life and reusability when devices were retrieved from treated households. The IHD is a digital picture frame that connects wirelessly to the subject's residential smart meter and home wireless network. The IHD reads the meter and displays near-real-time (8-10 second delay) electricity consumption, relaying this data to a complementary website and smartphone app. The

IHD cycles a slideshow of images the user can customize, such as personal photos, countdowns to upcoming holidays, and current weather; the company's theory is that more non-energy information and images on the device would encourage attentiveness towards the device. In addition to customized messages, the display cycles relevant details about electricity consumption: an image displaying current electricity use (kilowatt-hours and cost per hour in dollars); a bar graph displaying daily energy use (cost per day) for the last eight days; a bar graph displaying weekly energy use (cost per week); and a bar graph displaying monthly energy use (cost per month). Users interact with the IHD using an included wireless remote control. The user can navigate to a live energy dashboard, called Homeview, that displays instant electricity consumption and a line graph of the last 48 hours of data recorded by the IHD, including both 8-10-second demand (kW) data and 15-minute smart meter consumption (kWh) data. The display includes a toggle between cost (to the nearest $.01) or energy (instant demand measured in kW every few seconds or kWh measured every 15 minutes) and a toggle between a view of the past 48 hours or the last 5 minutes.

1.5.3.3 Incentive Treatment

Several previous studies and experiments have leveraged financial incentives using time-based rates made possible by the smart grid, and depend on the utility to change customer billing accounts to reflect this new rate design (Cappers, Spurlock, et al., 2016; Cappers et al., 2013b; Jessoe & Rapson, 2014; Jessoe, Rapson, & Smith, 2012). Due to timing and regulatory constraints for the study, it was impossible to create new time-based rates to test with research subjects in the utility service area; thus, necessity became the mother of invention. Time-based rates are fundamentally designed to motivate subjects to either conserve electricity or shift the timing of behaviors that drive electricity consumption to a more desirable "load shape" for a given DSM application (Breukers & Mourik, 2013). Figure 11 visually describes some of the load-shifting strategies a utility or grid operator may deploy to adapt to existing grid conditions. In our field experiment, load shifting and strategic conservation were the primary strategies.

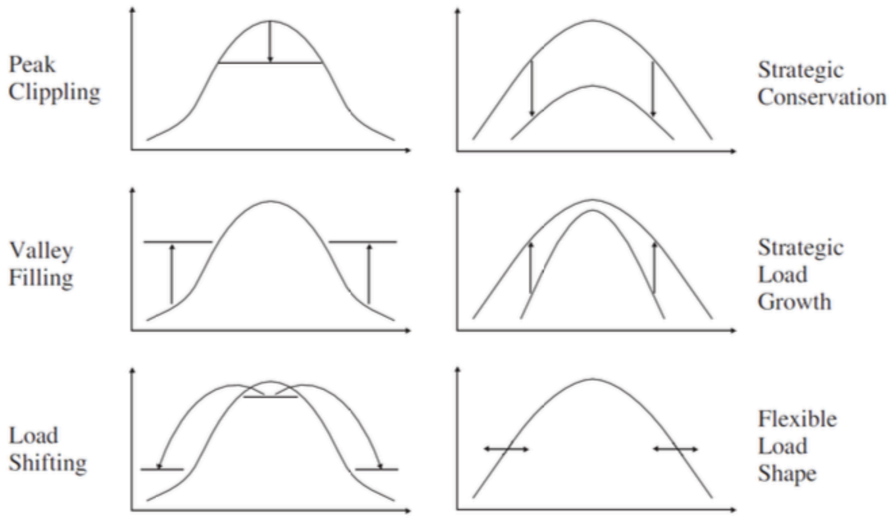

Figure 11: Load shifting options relating to time-based rates and demand response that may result from behavior changes (Breukers & Mourik, 2013).

There are many different time-based rates currently deployed or being tested around the world, including precise real-time pricing (RTP) that fluctuates with the market, flat rates that never change, fixed time of use (TOU) rates that have set peak and off-peak hours, or fixed peak-pricing that may be activated during risk of blackout at certain times (CPP) or variable times (VPP)(Faruqui, Hledik, & Palmer, 2012). Of all possible options, the peak-time rebate (PTR) is a rate design with minimal risk to the customer while still yielding potential benefits for grid operators looking to deploy demand response strategies (see Figure 12) (Faruqui et al., 2012). Additionally, competitions have shown promising results as behavior based efficiency strategies, including populations with college-aged participants (Petersen et al., 2007; Vine & Jones, 2016). Given that a true time-based rate wasn't feasible for the experiment, and taking these rate designs into account, a novel competition structure was defined to motivate general energy conservation and mimic the intention of a PTR structure, in which customers who reduce their energy from a baseline during set peak usage periods receive a rebate (Faruqui et al., 2012). This type of motivator or reward could be considered a "competitive performance-based financial incentive" because a customer's reward/payback was defined by both their own performance relative to the rest of the group and the amount of their actual bill.

All subjects randomly selected to receive the incentive treatment were notified by email in February 2015 with a message providing instructions on how to win up to two different incentive rewards; after this point, the subject was considered "treated" and was left to decide whether to try to win one, both, or none of the rewards associated with the incentives. The instructions described two basic tasks: (1) Reduce overall consumption for the duration of the study; (2) Shift the timing of consumption away from "peak hours" during specified "peak events" on random weekdays, announced via email, occurring 1-4 times a month (see Appendix B: Incentive Instructions for details).

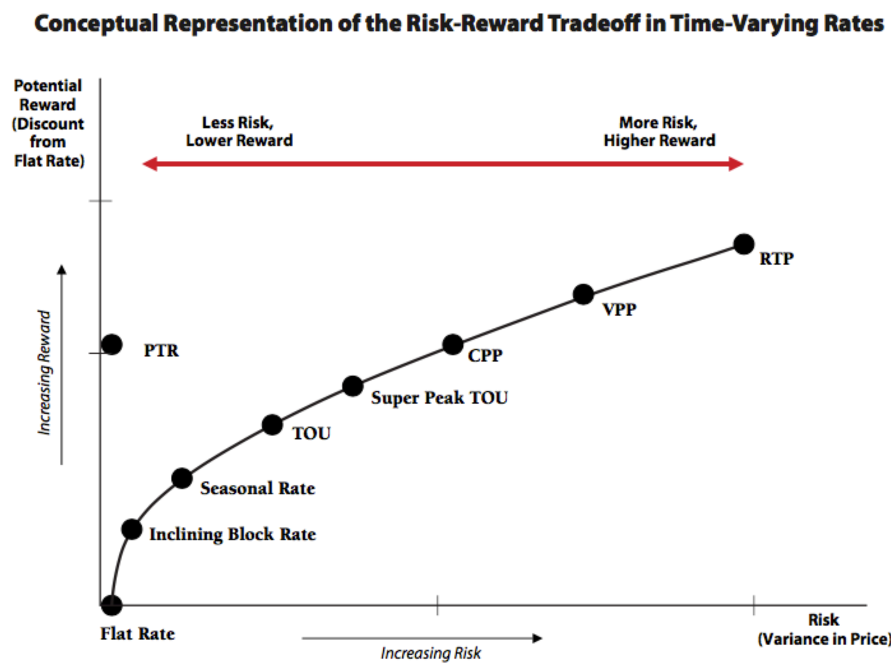

Figure 12: Conceptual risks and rewards from time-based rates (Faruqui et al., 2012). Peak-Time Rebates have low risk to customers but may provide better savings than typical rate designs; they inspired the field experiment's incentive design.

The instructions also stated the rules on how a subject could win money for each task. For energy reduction, daily energy use during the study period would be compared to a daily baseline derived from subject's energy use prior to the start of the study. Measured monthly during the study (February to May), the sum of daily changes from the subject's daily baseline would be calculated (e.g., 31 daily percent-changes summed to one score for March). The subject's total monthly energy reduction score would be ranked in comparison to other households in the study and if the subject's score indicated a net energy savings, a percentage of the subject's electricity bill that month would be reimbursed based on their percentile ranking in the group rounded to the nearest $5. For example, consider three subjects each with $100 bills in one month who ranked in the 1^{st}, 5^{th}, and 100^{th} percentiles of the treatment group based on their own behavior changes: the first subject (1^{st} percentile) would be reimbursed $100*(1/**1**) = $100, their full bill, while the second (5^{th} percentile) would receive $100*(1/**5**)=$20, and the third (100^{th} percentile) would receive $100*(1/**100**)=$1 (and then rounded up to $5). Subjects were also reminded in these messages that top-ranking households would be reimbursed for their entire bill. Theoretically, it was expected that subjects would recognize that if they pursued this challenge, they would save money by conserving energy and, if they ranked in any way, at least a portion of their bill would be reimbursed.

For the energy-shifting incentive, subjects were informed that for each peak event, electricity used during peak hours would be compared to what the subject's home typically consumes during these hours (called the "peak baseline"). For each month in the study, the total change from subject's peak baseline during peak events would be calculated. The subject's ability to shift energy use away from these peak hours would be ranked in comparison to other households in the study and the rank of the subject would determine whether they were awarded any money. This reward was different from the previous reward in that the share of daily energy shifted - not reduced - determined a single prize for each event rather than a portion of energy consumed. Ultimately a subject could win by simply changing the timing of when energy was consumed rather than reducing overall energy, so a prize of $20 was offered to the single winner from each event.

If the subject also received an IHD, they could track progress relative to their personal baseline displayed on the IHD screen, thus they received both more frequent feedback about their energy use as well as energy use relative to the metric of the energy reduction prize. Incentive messages were delivered to all incentive treatment subjects via email three times during the study period on different days of the week to account for varying schedules, but occurred from 5-7 PM, the time determined by the utility to be when real peak events often occur in the service area. IHD recipients were expected to have the added functionality of alerts on the IHD screen and on the associated smartphone applications, a service usually managed by the utility but in this case managed by CEIVA.

1.5.3.4 Historical Energy Data

All subjects had smart meters that collected data at 15-minute intervals in kilowatt-hours (kWh), or 96 observations per day. The utility provided historic data for each subject up to two years prior to the start of the study (October 2013) but limited to their tenure at the current location. For example, if a subject lived at one location starting in August 2012, data would be provided from October 2013; if the subject moved into their home in July 2015, data would start at that point. Since the subjects were renters, and predominantly undergraduate students, most of the subjects began their tenure at their current home in June 2015, but all subjects had data available starting in late August 2015, just before the semester began. Most subjects remained at their current location until the end of the study, in May 2016, giving the most complete set of energy data including all subjects a range from August 2015 through May 2016, or approximately 9 months (this constitutes approximately 7 million rows of data). The utility provided an additional anonymized control group of data (excluding study participants) from the entire residential population, approximately 440 million rows of data for the study period.

1.5.3.5 Survey Data

Two survey instruments were used: one for preliminary subject screening and selection, including baseline behavioral measures, and one administered to subjects at the end of the study period. Questions are derived from the energy cultures literature (Stephenson et al., 2010; Sweeney, Kresling, Webb, Soutar, & Mazzarol, 2013), value-belief-norm (VBN) theory (Stern, 2000) and the theory of planned behavior (TPB) (Ajzen, 1991) intended to understand the context of energy use and energy behavior changes mentioned in previous work (Abrahamse & Steg, 2011; Fornara, Pattitoni, Mura, & Strazzera, 2016,@lynham_why_2016; Karlin et al., 2016; Sintov & Schultz, 2015). See Appendix A: Survey Instrument for details of each question asked both before and after treatment. Survey question groups were divided into the following 5 sections: study eligibility, about your home, influences, energy use and your home, and about you.

In the "study eligibility" section, we ask questions that help screen out incompatible participants for the study. First we asked about the respondent's relationship to the university (undergraduate student, graduate student, medical student, faculty/staff, alumni, living with a university student, no relation, or other) and asked the respondent to choose the best-fit answer. For example, if the respondent was a full-time staff who happened to be taking graduate courses, they should choose faculty/staff. Next we ask a series of yes/no questions: if they live off campus, if they rent or own their local residence, if they have wireless internet at home, if they have access to a iOS or Android smartphone or tablet. These questions helped screen for ability to receive real-time feedback about household electricity consumption. To determine how to access and match energy consumption data from the utility to the response, we then ask who is listed as the account holder on the respondent's electricity bill, and they choose one of the following: "I am listed as the electric utility account holder," "A parent or guardian who does not live in my home," "The landlord/owner of my home," "Someone who lives with me is the utility account holder," or "I don't know who pays my electric utility bill." If the response includes an answer in which the respondent is not the account holder, the survey then asks for the name, email, and phone number of the account holder. It was assumed by the research team that it would be easier to provide contact details for the account holder than retrieve the account number; the utility would provide matching later on.

In the "about your home" section, we first ask what best describes the respondent's home's property type (Single family home, Duplex, Apartment/condo - 4 units or less in building/community, Apartment/condo - 5 or more units in building/community, Boarding house/individual room rental, Fraternity/Sorority chapter house, or Other). We then ask for an estimate of the home's size, in square feet. We then ask how many people live in the home, including the respondent, with response fields for adult (18+) males, adult females, and children. Next, we ask the respondent to indicate numerically how many of the following appliances and devices are in the home: dishwasher, refrigerator, mini-fridge, flat-screen (LED, LCD, etc) television, non-flat-screen television, clothes dryer, clothes washer, video game consoles, programmable thermostat, central air conditioner, or small in-window air conditioner. We list these devices and appliances as a way to ground-truth whether respondents plausibly have experience using certain appliances when they answer questions about perceptions of appliance energy use later in the survey.

If respondents previously answered that they rent their home, they were then asked to indicate whether common utilities (electricity, heating fuel, water, internet, television, or phone) were each included in rent or not. This question helps ascertain whether households may experience a split-incentive problem when it comes to energy efficiency. Respondents are then asked to indicate the primary source of heating fuel in their home, choosing one of the following: natural gas, propane, electricity, firewood/stove, no heating fuel, I don't know, or other. The final question in this section asked if the respondent has ever been exposed to information or education about home energy efficiency (in class, through the media, from an electricity company, etc.). This was asked to streamline the survey experience later on, i.e., if the respondent had no experience or exposure to energy efficiency, certain questions would have no meaning.

The "influences" section of the survey is designed to help understand where respondents get their information about energy and what influences their use of energy. The first question asks how knowledgeable the respondent is on the topic of energy efficiency, from "not knowledgeable at all" to "very knowledgeable." We then ask respondents to rank how helpful they find the following potential sources of information about energy efficiency: internet, friends or family, professors or classes, local utility companies, Efficiency Vermont (a local organization), and Newspapers or Magazines. Next we ask how often they discuss energy efficiency with friends, family, or neighbors (5-point scale, never to very often). Next we ask respondents to rank how much the following people influence their decisions about energy use: friends, neighbors, professors or teachers, work colleagues, and family. We also ask how important the respondents' home energy efficiency and costs are to them, choosing from very important, somewhat important, not very important, or not important at all.

In the "energy use and your home" section we first ask to rate, in their opinion, how energy efficient their home is on a likert scale (5 values, not efficienty at all to very efficient). We then ask if the respondent has every spoken to their landlord (or property manager, if not a rental) about the energy efficiency of their unit. We then ask the respondent to numerical estimate how frequently they do the following actions that might consume electricity: dry clothes in the clothes dryer (loads per week), run the dishwasher (times per week), dry hair with hair dryer (times per day), watch TV or other media source (hours per day). We also ask how often the respondent does certain energy-saving actions (on a likert scale: never, rarely, sometimes, often, always, N/A): pull the window curtains at night to retain heat, switch off lights in empty rooms, add layers or a blanket to stay warm at home, shorten showers to conserve hot water, change thermostat settings to conserve energy, unplug devices when not in use. Next we ask respondents to rate how likely they will be to do the following actions in the future (on a likert scale: not at all likely, slightly likely, moderately likely, very likely, I don't know): seek out information on how to conserve energy at home, talk to a landlord/property manager about efficiency upgrades, change home thermostat settings to conserve energy, insulate windows with plastic, unplug devices not in use, turn off lights when leaving a room, reduce shower time to conserve hot water, use additional clothing or blankets when cold. This previous set of questions were intended to help triangulate aspects of what study participants "think, have, and do" related to energy as part of the Energy Cultures framework (Stephenson et al., 2010) to be discussed in future work not directly connected to this dissertation.

Finally in this section, we ask respondents to estimate how many units of energy 11 devices or appliances (a CFL, an LED light, a laptop computer, a smartphone or tablet charger, an electric clothes dryer, a portable space heater, a room air-conditioner, a central air conditioner, a dishwasher, a standard refrigerator, a hair dryer) typically use in one hour. To help respondents make these comparisions, we provide an example that a standard incandescent light bulb uses 100 units of energy in one hour. This was chosen based on Attari et al (2010) who found this example best aided understanding.

1.5.3.6 Incentive and Study Communications

Common to any email marketing campaign, the email system used to broadcast incentive messages collected data per subject in terms of when and how often emails were read. This data was used to detect whether messages were received by participants and can be used in modeling approaches to relate email open rates to experimental outcomes like reductions in energy used during a demand response event.

1.5.3.7 IHD Connection data

In addition to energy usage data from smart meters, connection logs were provided by the IHD maker to determine whether a device was successfully connected. This was used to remove subjects from analysis who did not have successful connections to their IHD during the treatment periods. The IHD manufacturer, CEIVA, indicated that the device, while powered on, used drew very little electricity and would not increase participant electrical consumption significantly.

Paper 1

Bypassing the split-incentive problem? The interaction of feedback and incentives in renters' potential behavior-based energy savings

Expected publication: Nature Energy

Abstract

The smart grid is expected to facilitate a transition to more renewable, distributed energy resources by giving power system operators the means to manage energy supplies at the grid edge. Despite these technological advances, supply constraints caused by renewables displacing less intermittent baseload resources will require improved demand side management and thus deeper understanding of consumer behavior. Financial incentives, such as time-based electricity rates, represent one neoclassical economic approach to optimize rational consumer behavior. Competitions (games) and behavioral nudges may offer additional cost-effective solutions for demand response. This paper presents results from a randomized controlled field experiment in which rented residential households were presented competitive performance-based financial incentives (i.e., rewards were based on a household's rank relative to a group) to shift energy consumption away from a utility-designated peak period and/or real-time feedback via an in-home display (IHD). Results indicate that those who only received the IHD experienced an initial savings that wore off but, when incentive recipeints also had an IHD, these renters experienced a doubling energy savings while IHD-only homes' savings wore off. These results provide more evidence of how a specific and growing residential segment of consumers may be able to contribute to cost-effective demand side management solutions based on behavior changes despite the presenve of split-incentive problems, yet more rigourous research is needed in this area to avoid perverse incentives.

2.1 Introduction

Many consider that having more information leads to better and more efficient behavior. Feedback plays an important role in motivating residential energy consumers to alter their consumption patterns. Feedback, through various delivery systems and cadence, has been shown to be a promising tool to drive reductions in energy consumption either through curtailment practices or efficiency investments (Ehrhardt-Martinez et al., 2010; Foster & Mazur-Stommen, 2012; Karlin et al., 2015b). However, much of the literature evaluating the role of feedback contains inconsistencies and lack of clarity in the reporting of experimental design, data collection, analysis method, and results making it hard to draw strong conclusions quantifying the benefits of feedback on energy consumption (Karlin et al., 2015a). There have been cases where feedback causes increases in energy consumption (Matsukawa, 2004; Robinson, 2007). As more researchers rely on these protocols, and as the protocols evolve, we can expect more rigourous insights. Thorough reviews and meta-analyses have been conducted of existing utility-run Behavior-based (BB) program evaluations across hundreds service territories ,e.g. Mazur-Stommen & Farley (2013). Experimental evidence from many of these intervention methods (Darby, 2006; Ehrhardt-Martinez et al., 2010; Fischer, 2008; Karlin et al., 2015b; Vine et al., 2013; Vine & Jones, 2016) suggest that BB programs can cost-effectively deliver potential average energy savings of 4-12%, sometimes much more, although these higher estimates are often due to less robust research designs (Delmas et al., 2013). When real-time feedback at the household level was used in previous experiments, savings averaged closer to 9% (Ehrhardt-Martinez et al., 2010; Foster & Mazur-Stommen, 2012; Karlin et al., 2015b; York et al., 2015). Smart meters can play a role by providing residential utility customers access to their consumption information in near real-time (Koliba et al., 2013).

Smart meters (and the smart grid) are expected to support a cleaner, more efficient, energy system largely based on distributed energy resources relying on wind, water, and solar energy supplies. These meters collect data with high-frequency compared to historical utility billing practices; where data had been collected at monthly intervals by a meter-reader, smart meters collect data at sub-second intervals (usually storing it at 15-minute or hourly intervals). This is expected to enable a more efficient pricing scheme where all utility customers can pay rates closely aligned with the timing of the electricity supplied. Time-of-use rates may provide additional value to both utility managers and ratepayers, seen through more predictable consumption patterns and financial incentives to reduce or adjust consumption (Cappers et al., 2016).

Those results, suggesting benefits and challenges of both feedback and time-based rates, are broadly applied; distinct populations have not investigated closely. Renters are a growing segment of the housing market and a larger share of low-income households that have greater energy burdens (Joint Center for Housing Studies of Harvard University, 2015). Renters are often members of so-called vulnerable populations, including the elderly, low-income, and chronically ill, and there is limited research understanding how this population experiences time-based rates (Cappers et al., 2016). There is a need to find ways to help this population participate in efficiency programs, or identify new programs that can succesfully motivate this segment to become more efficient. Using methods recommended in the literature and by the US Department of Energy, this paper attempts to quantify savings from a class of renters (millienials and off-campus college students) by describing and analyzing results from a field experiment involving real-time feedback and financial incentives to reduce and/or adjust energy consumption.

2.2 Methods

The following section describes the methods and experimental design used to carry out and analyze the field experiment, including the recruitment strategy, data collection, interventions used and their timing, and analysis approach. The experiment was designed as a randomized controlled trial (RCT) in which subjects were randomly assigned to one of four groups. Each group received up to two separate interventions: a real-time energy feedback intervention, an incentive intervention, both interventions, or neither (the control group).

2.2.0.1 Feedback intervention

Feedback was delivered through an in-home display (IHD), a form of home energy monitor. The IHD was a digital picture frame, produced by CEIVA, that when connected to the home's smart meter and wireless internet, can provide real-time energy feedback that typically updates within ten seconds. When each participant first configures the IHD, the picture frame automatically cycles images that display measures of hourly energy use along with a standard set of images. Upon completing the setup procedure, there is an included energy dashboard that shows instant feedback on both energy use and costs. Participants would have to use a small remote control included with the IHD to navigate to this dashboard, but the default setting is to cycle various views into the home's energy consumption such as daily average use for the last 7 days or current use (usualy in dollars). Users could also customize the picture frame to show personalized photos, news, and social media feeds, if they chose to do so. Along with the IHD, there was a supplemental mobile app and website that the participant (and their roommates) could access from anywhere with an internet connection, which was equivalent to the frame's energy dashboard and provided extra functionality using the mobile device's touchscreen. CEIVA's IHD was ultimately chosen because it was compatible with the partner utility's infrastructure, had reasonable costs for the scope and budget of the field experiment, and included a variety of channels to provide feedback; rather than emphasize or differentiate between the nature or type of the feedback provided, the intention was to ensure particpants could receive feedback in a way that was personally most salient to them.

2.2.0.2 Incentive intervention

The incentive treatment was intended to model a peak-time rebate incentive design in which participants are compensated after completing a desired task (e.g., avoiding energy use during a DR period) and was chosen due to its relatively low risk to ratepayers (i.e., no penalty for inaction) and ease of implementation (Faruqui et al., 2012). Due to the relatively small sample size and regulatory process in Vermont, a custom rate could not be defined for this experiment. The incentive contained two separate pathways to be compensated and was initially delivered via an email message; this message marked the beginning of Phase 2. Participants were informed in the opening email that they would be rewarded based on their performance reaching two goals. One ongoing goal asked them to do their best to conserve energy over the 3-month period while the other simulated a series of demand response events in which performance during the event would be rewarded like a peak-time rebate. Their daily energy use during this time was compared to their own home's average daily energy use in Phase 0 as a daily percentage change. For example, if one home's average daily kWh was 10 in Phase 0, and on one day during Phase 2 the home used 9 kWh, that day would have a score of -.1 (which is the percent-change from baseline). This value was totaled for each of the three months, and compared to everyone else who got the treatment. If this value was negative, implying a net energy savings, a home's position in this comparison, e.g. 1^{st} percentile (most savings) or 100^{th} percentile (least savings) would earn them a portion of their energy bill paid to them rounded to the nearest \$5. For example, a home with a \$100 bill in March that was in the 1^{st} percentile of savings would earn 100% of their bill and receive \$100, while a home with a \$100 bill in March in the 100^{th} percentile would earn 1% of their bill (rounded to the nearest \$5) and received \$5. Participants were also asked to pay attention to their email accounts for a "peak event" alert. Participants would be informed 24 hours in advance of the event, which was when they would need to reduce their energy consumption for a period of time. The household that reduced the most from their Phase 0 baseline during those hours would earn \$20. Our peak events were called on 3 random weekdays at the end of April, the events happened between 5 and 7pm, resulting in a total of 2 hours to avoid energy use per event.

2.2.0.3 Participants

Since the experiment tested a potential response to energy feedback and/or incentives, each participant had to be able to receive these interventions whether or not they were assigned a treatment. A pre-treatment survey that included screening questions for eligible households was used to exclude households that would have no ability to respond to our treatments. These questions asked specifically about renter/homeowner status, wireless internet connectivity in the home, and whether participants had access to an iOS or Android phone or table. The target population was intended to be renters with in-home wireless internet and smartphones or tablets. Survey respondents who did not indicate always-on wireless internet or access to these mobile devices were disqualified from participating while homeowners were allowed to continue in the pilot. The pre-treatment survey also asked questions about household demographics, knowledge of energy efficiency and energy-saving behaviors, and perceptions of appliance energy consumption. Most of these survey results are discussed elsewhere (see Palchak et al (n.d.)), except for those relating to perceptions of energy consumption, which are discussed in Fredman et al (n.d.-b).

2.2.0.4 Data collection

Data was collected from Fall 2015 through Spring 2016 (a total of approximately 9 months) and included three "phases" that were defined by the terms of typical renter tenancy in the participating utility service area. Figure 13 shows the progression of these phases. The pre-treatment period (Phase 0) ran from September 2015 to early December 2015, approximately 3 months. Phase 1 took place from early December 2015 to early February 2016, also approximately 3 months; during this phase, subjects were either considered treated if they had IHDs installed and control if they did not. Phase 2 was the next 3 month period from early Februarty until the end of April and included IHD and Incentive treatments. Personally identifiable information for each participant was retained separately for program management purposes (e.g., ensuring incentive payments) and was destroyed.

Besides 15-minute AMI data provided by the utility, the IHD maker also provided connectivity logs of each device that included any gaps or lapses in IHD functionality. The logs included timing of when each participant used the accompanying mobile and web apps; this information was tied to the

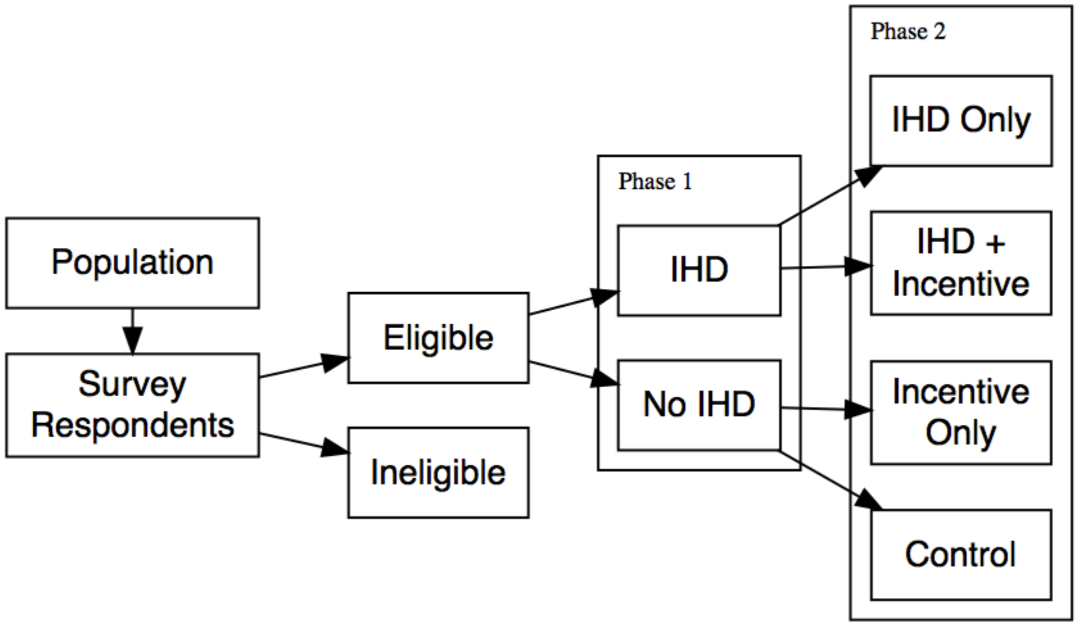

Figure 13: Flow of respondents into treatment groups.

IHD's serial number so it was impossible to know if it was the participant who joined the study (the utility account holder) logging in or someone else living with the participant. The email marketing service MailChimp (MC) was used to send messages to participants. MC provides an application programming interface (API) that was used to obtain email opens for each participant.

2.2.0.5 Treatment deployment

IHDs were deployed over two waves in December 2015 and January 2016. A random selection of the eligible population was invited via email to pick up an IHD in mid-December; this first invitation marks the beginning of Phase 1. Figure 14 reflects how variations in timing of device installation were balanced randomly in both IHD treatment groups. In phase 1, for the IHD groups, darker shaded areas indicate when the IHD setup was completed for each participant. If participants with IHDs were unable to complete the installation process or did not maintain connectivity throughout both phases, they were removed from the analysis. Later in mid-January, another random selection of the eligible population was invited via email to pick up an IHD. Anyone who was not eligible – and thus not offered – an IHD was excluded from the analysis. 50% of the first wave and 50% of the second wave were randomly chosen to also receive the incentive in Phase 2.

2.2.1 Panel Data

It was necessary to account and control for potential variability in participants and use the “cleanest” panel data possible, so a few steps were taken to prepare the dataset. The pre-treatment survey data and the records kept regarding IHD recruitment and deployment facilitated this. A key difference between renters and homeowners is their tenure in a given home; most leases for rental units in this study area are on an annual basis, although some may stay in their units for longer than one year. When these annual contracts begin will vary: most begin in June or August, and sometimes September or October (although this is usually not the case for college students, who are often settled in their housing by the start of the Academic year in late August). With this in mind, collected energy consumption data was consistently available for all subjects from the end of August 2015 (when the semester began) until the end of May 2016–this is roughly the entire academic year, as these renters were college students affiliated with the university. Before this period of time, some subjects had more than a year of data (e.g., graduate students or rising seniors staying in one location) and some had data past May 2016 as their leases (and thus their utility accounts) had not ended. Smart meter data was provided by the utility in 15-minute intervals (96 observations per day). After some exploratory data analysis comparing 15-minute, hourly, daily, weekly, and monthly summarizations, we determined the panel dataset should be defined as observations of daily energy consumption (in kilowatt-hours or kWh). This aligns well with the treatments, expected behavior changes to be measured, and reality; participants could feasibly makie changes in their daily habits and behaviors.

2.2.2 Attrition

The Hawthorne Effect, when subjects who know they are in an experiment act as they believe the researchers expect them to act, is a phenomenon that can confound the interpretation of experiments and research in energy domain is not excluded (Schwartz, Fischhoff, Krishnamurti, & Sowell, 2013). To attempt to account for this, anyone in the study who had not been initially invited to take out an IHD was excluded from the panel. This exclusion made it so everyone in the panel had been offered an IHD at some point, but those in the IHD treatment groups were the ones who accepted the offer. Thus anyone in the analysis was potentially aware that they were in an energy experiment. In some cases, participating homes that were given IHDs experienced installation or connectivity problems which could be observed by CEIVA's technical support team. To account for this issue in analysis, those homes given IHDs that did not have adequate connectivity during both treatment phases of the study were removed.

Figure 14 visualizes the panel and the experiment's treatment timing. Each row (observation) in the panel (illustrated in the figure) includes variables that facilitate regression models for analysis. These include details about the participant (including details of the home, e.g. how many adults live there and the self-reported size of the home in square feet), their treatment assignment (both the treatment group assignment and logical flags indicating whether they received an IHD or the incentive), the actual energy observation (date, kWh), and conditions of the treatment relative to the observation (e.g. whether the observation occured during a treatment period). These features were then be used to derive indicator variables and normalize energy values for analysis when necessary.

2.2.3 Analysis

Our goal was to examine and quantify the potential changes in energy use associated with the two interventions deployed in this field experiment, including any potential interactions.

The DOE Universal Methods Project's Residential Behavior Protocol (Stewart & Todd, 2017) and

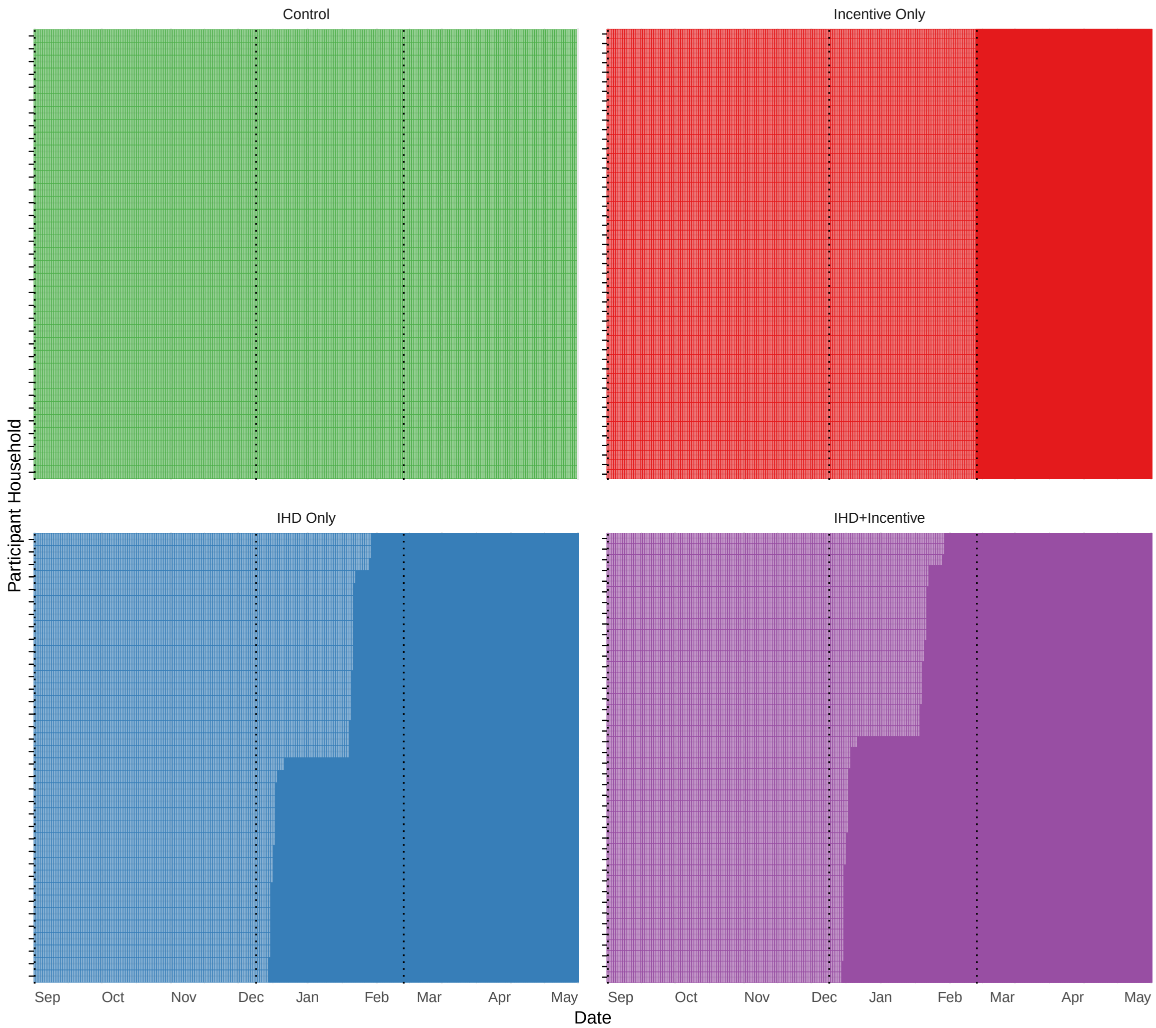

Figure 14: Participant households and treatment timing. Each row is a participant, vertical dotted lines indicate when invitation to obtain IHD was sent (Phase 1 begins) and when incentive email initiation was sent (Phase 2).

SEE Action Behavior-Based EM&V report (Todd et al., 2012) recommend the use of Randomized Control Trial (RCT) methods and related evaluation techniques to identify energy savings from behavior-based residential interventions. We create two separate sets of panel data for each treatment phase and specify fixed-effects regression models to determine difference-in-differences average savings estimates from the incentive-only, feedback-only, and feedback+incentive treatments relative to the untreated group. Both panels include the pre-treatment (phase 0) data. The panel dataset for phase 1 examines participants who had the IHD and those who did not, while the panel for phase 2 examines separately one effect size on the two treatment conditions as well as the interactive treatment. These panel data observations are limited by the duration of the experiment (running from Fall 2015 through Spring 2016, approximately 10 months). This duration is shorter than other behavior-based protocols that recommend multi-year observations to offset the seasonality of certain aspects of energy consumption. While we deviate from these recommendations, it reflects the reality that renters often do not have year-over-year tenure (some participants lived in their households longer than 10 months, but this period – the academic year – was the longest consistent period available across all households, as some residents move in or out at different times of year). To account for this seasonal variability, we used time fixed effects, and to account for any unobservable variables in each household, we specify participant (sometimes called unit or subject) fixed effects. While the UMP recommends this approach, we first examined variations of OLS, fixed effects, random effects, and mixed effects linear models to make sure this was the most appropriate model with the best fit. Comparisons of these models indicate that the R^2 values for the time and participant fixed effects difference-in-differences model presented in this paper is the best fit, confirming that the UMP recommendation is appropriate. F-tests and Breusch-Pagan tests for time fixed effects were significant. Breusch-Pagan tests for cross-sectional dependence and heteroskedasticity were both significant so clustered robust standard errors were calculated in the panel models, which is also a recommendation in the UMP for residential behavior programs.

In phase 1, we closely follow equation #5 in Stewart & Todd (2017):

$kWh_{it} = \alpha_i + \tau_t + \beta_2 P_{1it} * TrIHD_i + \varepsilon_{it}$

α_i represents unobservable time-invariant aspects of energy used by each participant household i and are controlled for with subject fixed effects; time fixed effects (unobservable influences of each time step t on energy use) are represented by τ_t. β_2 is the average energy savings per time period on each participant. P_{1it} is an indicator variable that set to equal 1 for any time period t when participant i received the treatment during phase 1 and zero otherwise and varies for each household as seen in Figure 14. $TrIHD_i$ is an indicator variable set to equal 1 when the subject is in the treatment group.

In phase 2, equation #5 in Stewart & Todd (2017) is adapted to account for separate and interacting treatments:

$kWh_{it} = \alpha_i + \tau_t + \beta_2 P_{2it} TrIHD_i + \beta_3 P_{2it} TrInc_i + \beta_4 P_{2it} TrIHD_i * TrInc_i + \varepsilon_{it}$

Where additional specifications are added to account for effects from the incentive (β_3) and the interaction between the two treatments (β_4) and indicator variables for when treatments are active on treated households.

2.2.3.1 Coding and reproducibility

All data analysis and visualization was done using the R language and the `tidyverse` family of packages (R Core Team, 2017; Wickham, 2017). Specifically, fixed effects models were created using the `lfe` package (Gaure, 2013). This document was produced using the `Rmarkdown` and `Bookdown` packages (Allaire et al., 2018; Xie, 2018).

2.3 Results

Figure 15 plots the average daily kWh of households that received an IHD and those that did not during the pre-treatment period and phase 1. In this figure, dashed horizontal lines indicate the

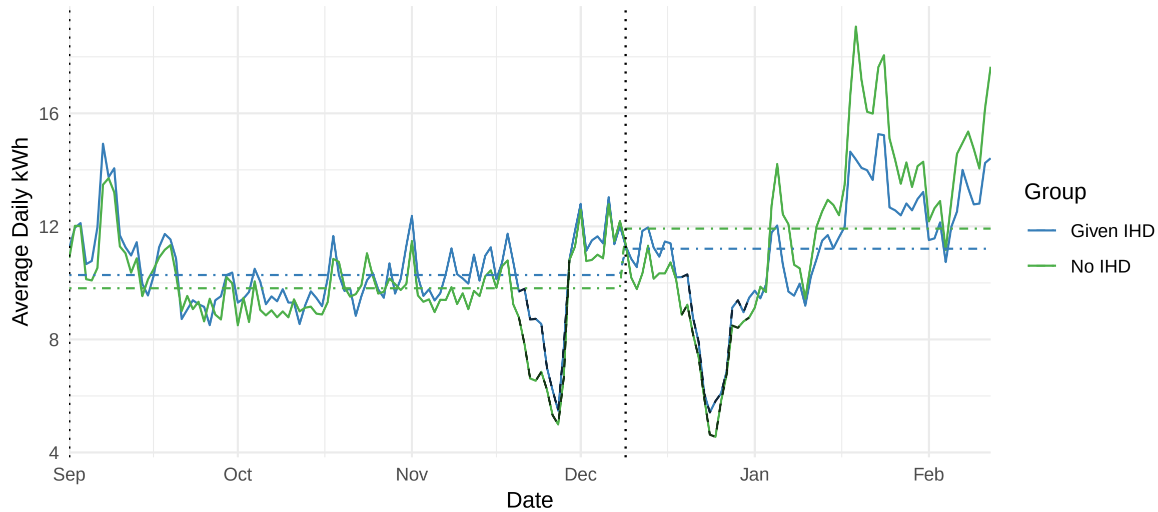

Figure 15: Time series plot of mean daily energy observations of homes given IHDs compared to those that received no IHD during treatment phase 1.

average daily kWh by group for each period. While there is variability in daily kWh throughout both periods, the groups follow similar seasonal patterns. Comparings the horizontal averages, households with IHDs appear to have experienced less of a step-up in average daily electricity consumption than those who did not. Carefully observing the dashed average lines in the figure, it is possible to see that the difference between the control group in these phases are larger than the difference between the IHD group. Average daily electricity consumption varies subtlely by treatment group and phase of the study period. All groups experience drops during "holiday" periods (the week of Thanksgiving, the time leading up to and from Christmas eve through New Years Eve, and the university's spring break). All groups experience a step-up from the pre-treatment period to the first treatment period when IHDs were installed, and it appears the two groups with IHDs experienced a less intense step-up. During the second treatment period, when incentive messages were delivered, the control group and combined treatment group experience step-downs from the first treatment period, while the IHD-only group experiences a slight step-up and the Incentive-only group experiences relatively little change.

The effect of the incentive on households, not accounting for IHDs at all, appears to be less significant than the IHD, if there is any effect at all. Figure 16 shows how average daily electricity consumption changes between households prior to and after the incentive message was delivered. While the average values are slightly different for each group, the step-up in energy use that occurs between periods appears to be about the same. Despite these similarities, this figure does not account for the fact that in phase 1 approximately half the group labeled here as “Given Incentive” also had the IHD, and half the group labeled “No Incentive” also had IHDs.

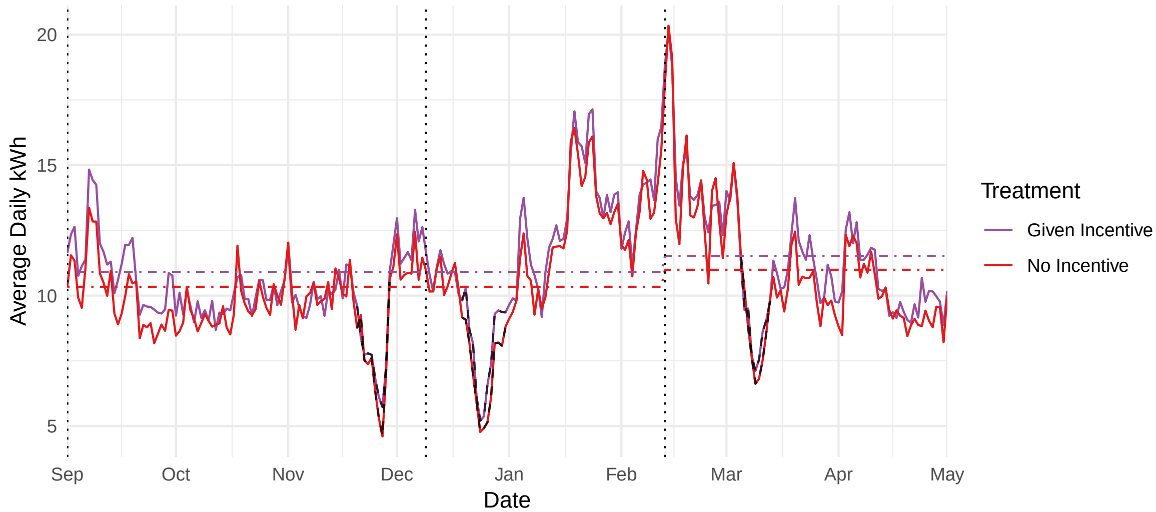

Figure 16: Time series plot of effect of Incentive compared to households who received no Incentive during treatment phase 2.

We can look at changes between each specific treatment group, too. Figure 17 shows the observed average daily kWh for each individual treatment group. It is possible to see how seasonal characteristics influence each group roughly the same way, although there are some subtleties. For example the spike near the begining of phase 2, likely caused by a series of extremely cold February days, is more pronounced in the Control group and least pronounced with the IHD Only group.

Figure 18 illustrates the relationships of changes between treatment groups over the entire study period better than the timeseries plot without the daily fluctuations shown in Figure 17. We can see that the Control group occupies extremes in each phase, and the Incentive group gradually moves higher in each phase. Each group with IHDs experiences step-ups in consumption during

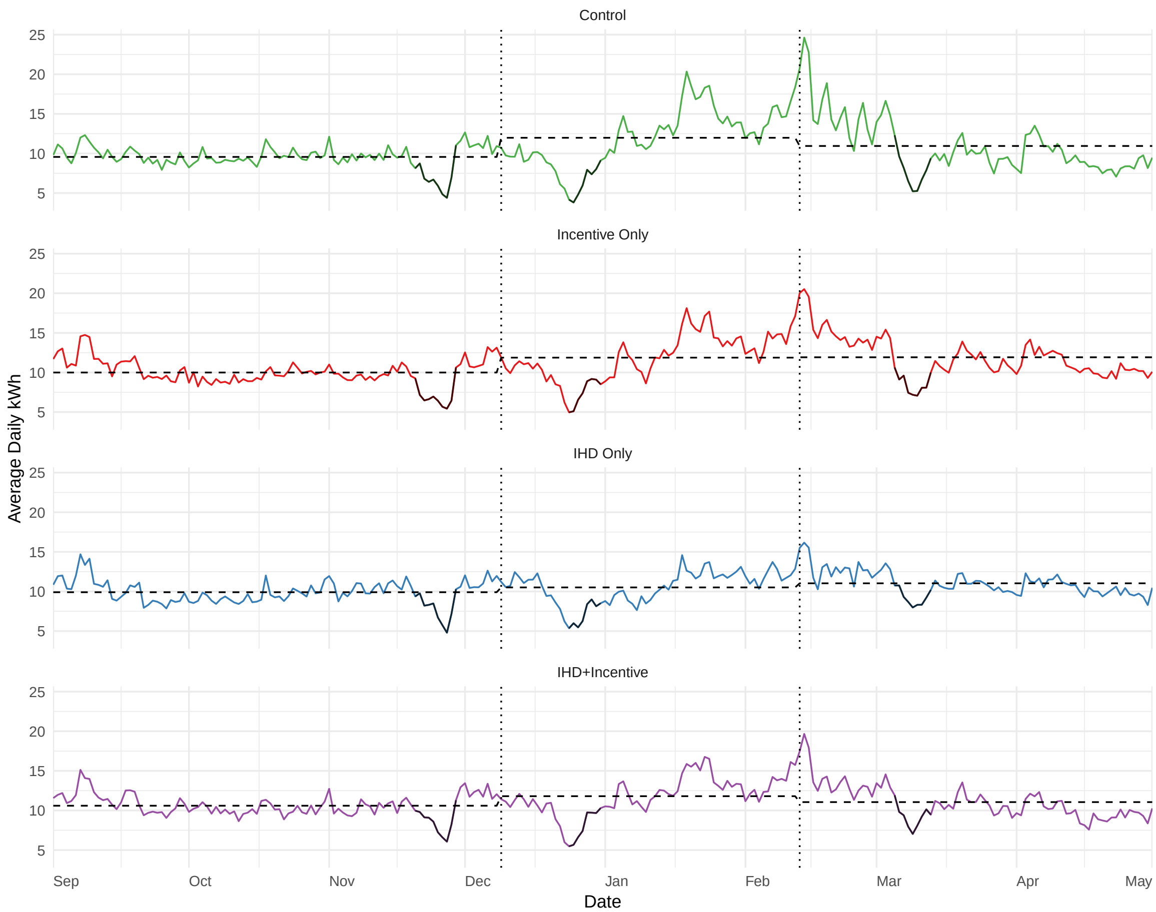

Figure 17: Timeseries of mean daily kWh for each treatment group. Horizontal dashed lines represent mean of all daily values for all subjects. Dashed overlay in timeseries marks holidays and official university breaks.

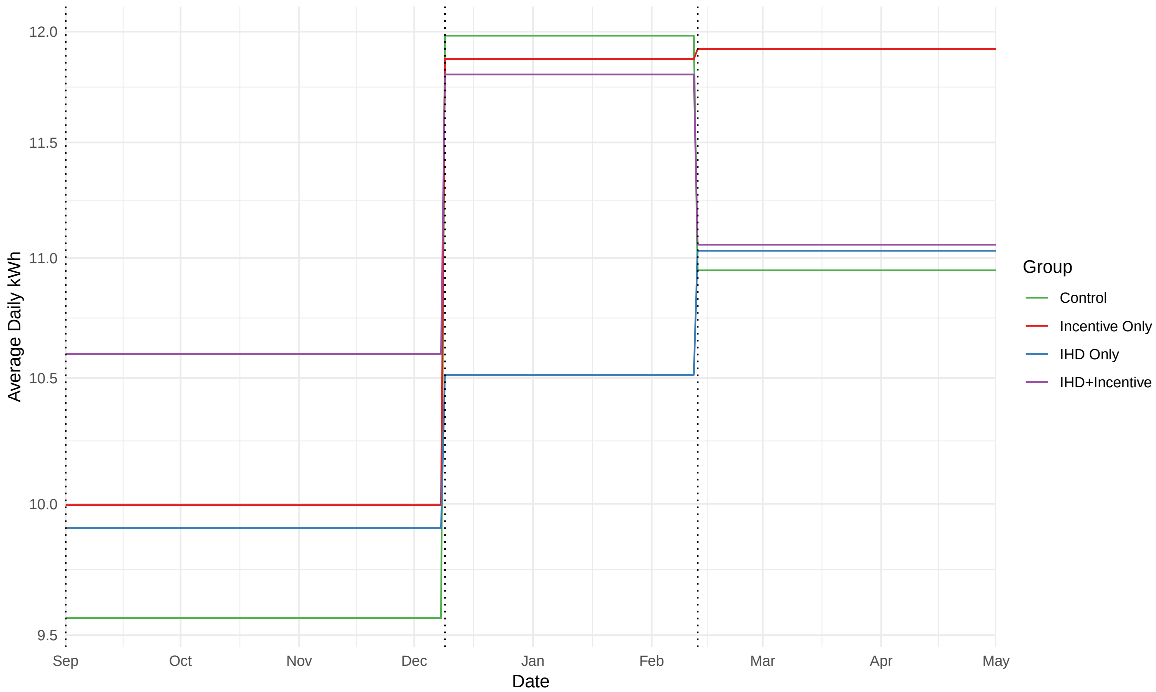

Figure 18: Average daily kWh by treatment group and period.

phase 1, albeit not as extremely as the Control group, yet the IHD+Incentive group steps down in consumption between phases 1 and 2 while the IHD group does not. While we can see visually there are differences between how these groups change through the treatment periods, the panel regression models will help quantify these changes.

2.3.1 Regression Models

2.3.1.1 Phase 1 : Initial feedback effect

This phase of the analysis ignores data taking place after the `incentive` message was delivered and seeks to understand if the presence of an IHD influenced energy consumption. We use a difference-in-differences (DiD) regression with fixed effects for both unit and time; standard errors are clustered on each treated unit. Based on the model specified in phase 1, the average treatment effect of the IHD was -8.94% and significant (p=0.068). Details of the model results are described in Table 2. The clearest relationship of energy savings during this period can be seen in Figure 19. Had the

Table 2: Phase 1 regression results.

	kWh	kWh/area	kWh/person
Feedback Effect	$-0.0894^{\cdot}$	-0.0015^{*}	$-0.0775^{\cdot}$
	(0.0490)	(0.0007)	(0.0407)
Num. obs.	26400	26400	26400
R^2 (full model)	0.7182	0.6339	0.6501
R^2 (proj model)	0.0031	0.0048	0.0034
Adj. R^2 (full model)	0.7147	0.6293	0.6458
Adj. R^2 (proj model)	-0.0093	-0.0076	-0.0090

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 3: Phase 2 regression model results

	kWh	kWh/area	kWh/person
Feedback	0.0567	-0.0004	0.0400
	(0.0545)	(0.0008)	(0.0465)
Incentive	0.0841	0.0001	0.0663
	(0.0582)	(0.0009)	(0.0501)
Feedback + Incentive	-0.1674^{*}	-0.0007	-0.1336^{*}
	(0.0718)	(0.0011)	(0.0621)
Num. obs.	28479	28479	28479
R^2 (full model)	0.7500	0.6483	0.6671
R^2 (proj model)	0.0044	0.0023	0.0042
Adj. R^2 (full model)	0.7470	0.6440	0.6631
Adj. R^2 (proj model)	-0.0075	-0.0097	-0.0078

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

IHD group demonstrated no difference relative to the control group, average daily kWh would be near the endpoint of the dashed line in this figure.

2.3.1.2 Phase 2 : Treatment Interactions

The second phase of the analysis examines the interactions between the feedback treatment and the incentive treatment, while also providing additional informatoin about how the IHD group's treatment effect may have changed over time. Based on the model specified in phase 2, the average treatment effect of the IHD was 5.67% and not significant (p=0.298). The average treatment effect of the incentive only was 8.41% and not significant (p=0.148). The interactive average treatment effect was -16.74% and significant (p=0.02). Details of the model results are described in Table3. Figure 21 shows the DiD comparison similar to Figure19. Table 4 compares results of both models.

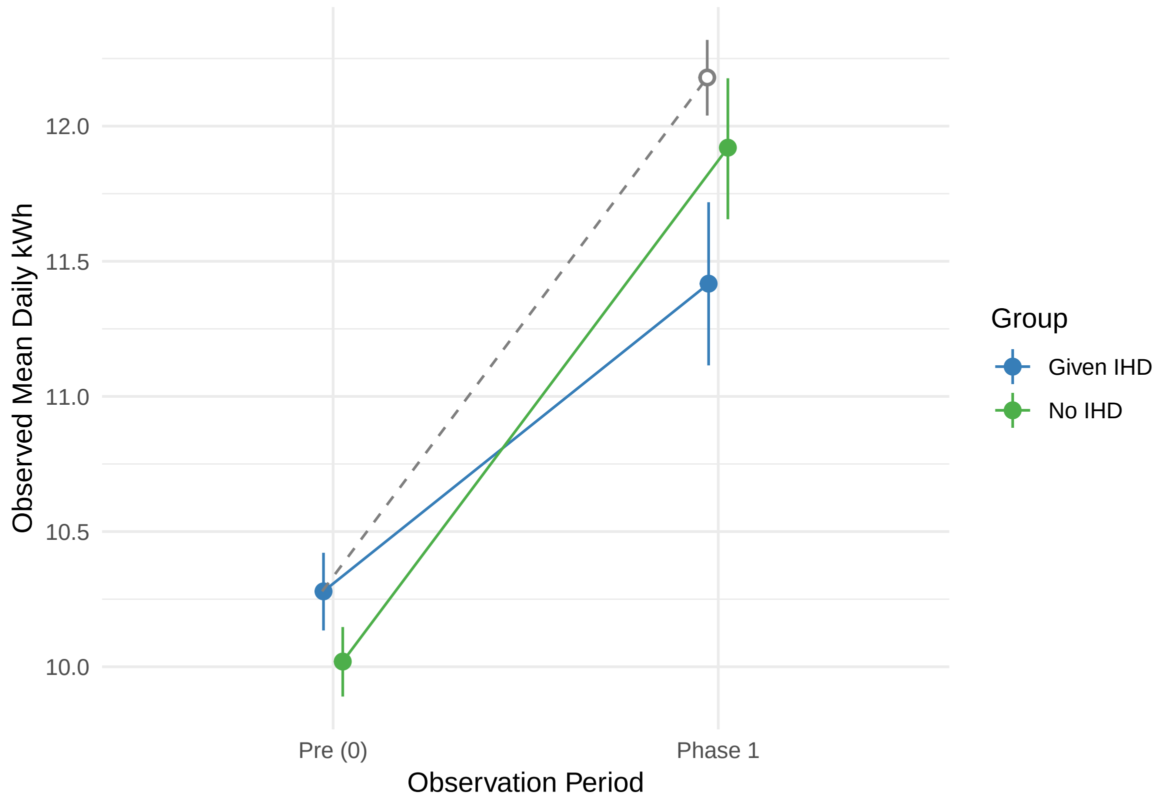

Figure 19: Bootstrapped (B = 5000) mean daily Kwh for each group during phase 1 with 90% confidence intervals. Dashed line indicates how the IHD group would have changed to be identical to the chances of the control group.

Table 4: Regression results from phases 1 and 2

	Phase 1	Phase 2
IHD Only	$-0.0894^{\cdot}$	0.0567
	(0.0490)	(0.0545)
Incentive Only		0.0841
		(0.0582)
IHD+Incentive		-0.1674^{*}
		(0.0718)
Num. obs.	26400	28479
R^2 (full model)	0.7182	0.7500
R^2 (proj model)	0.0031	0.0044
Adj. R^2 (full model)	0.7147	0.7470
Adj. R^2 (proj model)	-0.0093	-0.0075

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

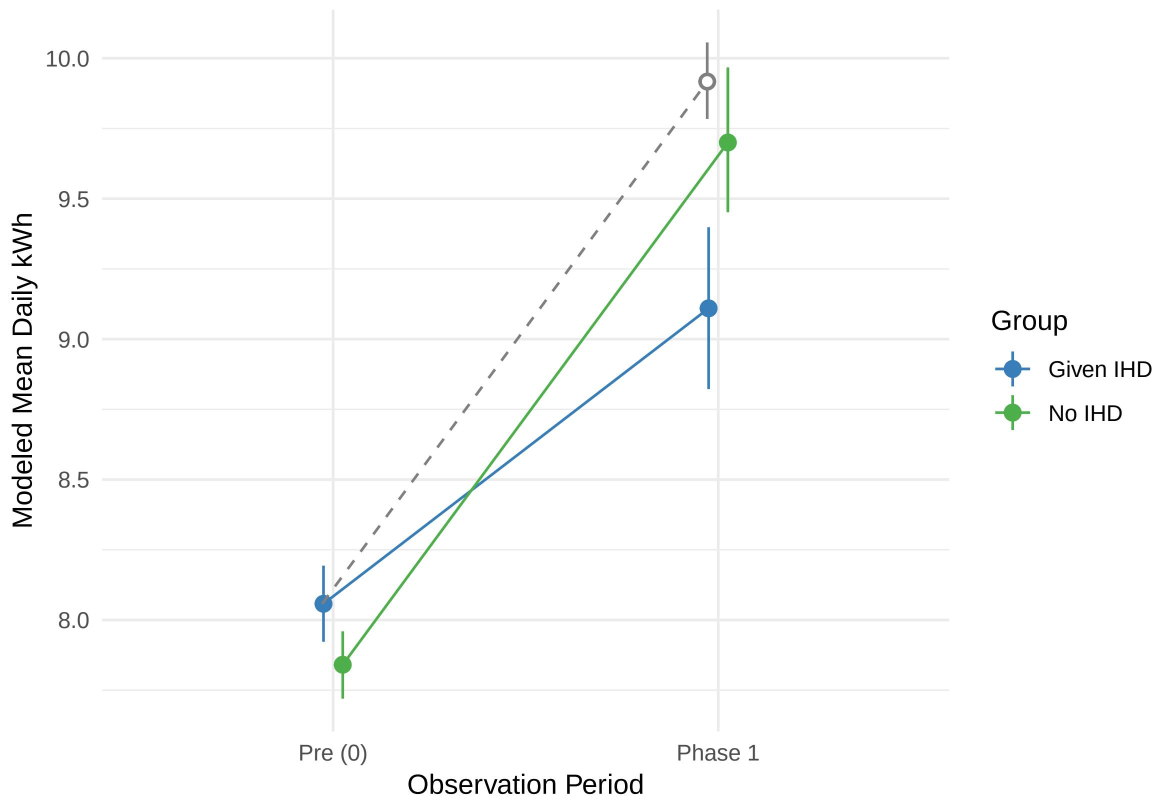

Figure 20: Bootstrapped (B = 5000) mean daily Kwh for each group during phase 1 with 90% confidence intervals. Dashed line indicates how the IHD group would have changed to be identical to the chances of the control group.

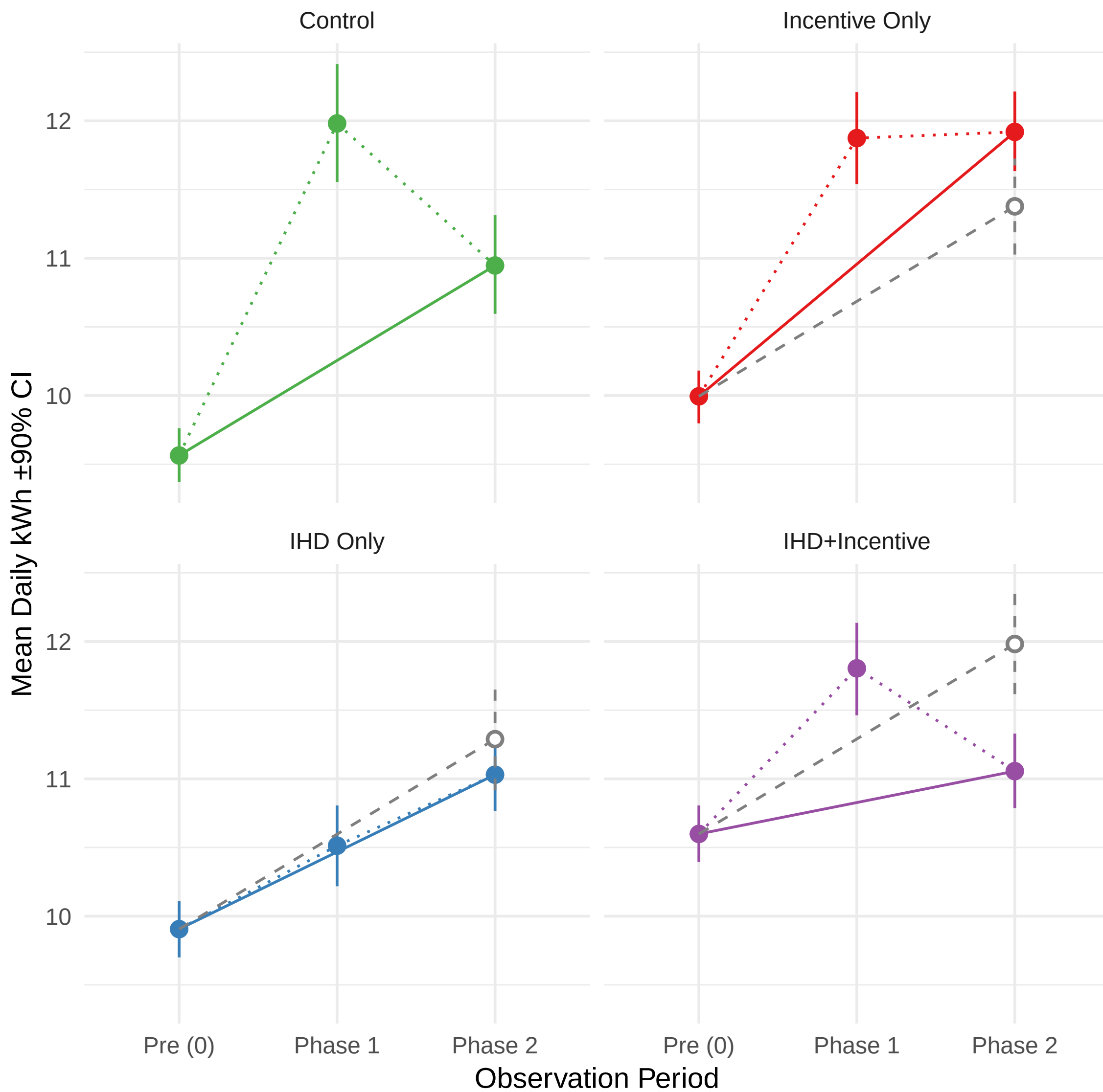

Figure 21: Bootstrapped (B=5000) mean daily kWh by observation period and treatment group, with 90% confidence interval, where solid line is the slope of change between phase 0 and phase 2. Dashed line indicates how each treatment group would have changed to be identical to the changes of the control group. Dotted line is the slope of change from Phase 0 to Phase 1 and Phase 1 to Phase 2, respectively.

2.4 Discussion

The results of this experiment indicate that there are differences between how financial incentives and feedback about household energy consumption interact to potentially induce or prevent renters from conserving energy in their homes. First, there is reasonable evidence from this experiment to suggest that renters respond to in-home displays and real-time feedback similarly to the broader population that has been exposed to these novel interventions similar to, e.g., Karlin et al. (2015b); Ehrhardt-Martinez et al. (2010); and Foster & Mazur-Stommen (2012), seeing initial savings around 8% in this case. As time went on, demonstrated by the IHD-only treatment groups in both phases, there was an initial signal of savings in phase 1 that subsided in the second phase, suggesting the group may have lost interest in the device. This is similar to other industry experiences that have been casually described a "mean time to kitchen drawer" effect in which the user no longer sees value in using the device, either because they believe they have learned what they could or no longer find the information compelling and stop using it, i.e., they put it away in the kitchen drawer (Walton, 2015). Second, there is stronger evidence that an interaction between incentives and feedback can produce potentially larger savings in this population. There was a portion of the IHD group from phase 1 that went on to receive the incentive treatment and effectively doubled their average savings during phase 2. Whether this type of savings persists remains to be seen and must be considered in future pilots and experiments, there was a reasonably strong confirmation that the group who received both treatments experienced energy savings. More should be done to test this in the future and explore whether certain household demographics or characteristics played a role in this effect. Theoretically it is possible that, as the effectiveness of the IHD began to wear off, the prospect of winning money, playing in a game, or some unknown reason compelled this group to pay more attention to the device. A clear takeaway is that while feedback fundamentally works, perhaps by helping the user optimize their behavior, it is temporary; the prospect of a reward–in this case, money–could be the form of engagement that helps maintain attention on the feedback, allowing the feedback mechanism to continue working. More research is needed to disentangle why the feedback wears off. Is there something undesirable about the feedback (e.g., the pricing display) or the technology itself, leading the user to stop paying attention? The fading effectiveness observed in the group that only received the IHD might be an indication that the feedback functions more as a guide than a training tool, or perhaps the learning users receive, when displayed as minimal energy expenses (e.g., electricity costs of two cents an hour) crowds out their motivation to conserve energy because the value is so low. Individuals may not be adequately learning, but they may be learning and deciding it is not worth the effort? In this sense, the financial incentives may buttress their motivation to utilize the feedback and identify savings opportunities. These tensions are explored further in Palchak, et al. (Palchak et al., n.d.)

Surprisingly, the incentive group demonstrated the strongest negative savings effect of all treatment groups. Although the statistics suggest this was a marginally significant change and may be due to random circumstances of the experiment, this response should give those who work in the energy industry pause. When presented with fairly clear, reasonably easy requests to adjust or conserve energy consumption, this group ended up using more energy than the untreated group as well as the groups receiving feedback. On one hand, if this result persists in similar future experiments, there may be something fundamentally wrong with standard economic theories about financial incentives; perhaps incentives like this create a sort of crowding-out effect decribed in Frey and Jegen where an incorrect financial incentive de-motivates action (2001). Unlike the groups that had IHDs, the incentive-only group had a weaker feedback signal (their monthly bills) to understand the impacts of any changes they made; the group with both treatments may have benefitted from having both a reason to pay attention to their behaviors (earn money) and the means to connect their actions to energy and financial impacts via the real-time feedback in the IHD. This suggests that something about having real-time feedback supports the task of making behavior changes that reduce energy consumption in the home. Perhaps this support system–a device with real-time feedback about energy use–enables the user to avoid crowding-out by getting instant gratification for changes made;

it's possible that the feedback acts as a guide for the user to see specific cost-saving actions after some trial-and-error (e.g., watching energy spike or decline during certain activities). This potential insight–that perceptions are changed by the feedback–is explored further in Paper 2.

There were some limitations with this experiment that future work could improve upon. We were unable to collect a full year or more of data as suggested by the DOE protocols. This is a reality that field experiments in this domain must grapple with as there is more dynamism in the renter population; individuals may not stay consistently in the same place or have the same household composition year-to-year even if the ratepayer stays (i.e., new roommates coming and going). However, the statistical benefits of fixed effects can account for unobservable variables and potentially mitigate the comparison between seasons. Utilities can do more to adequately capture these changes in their customer information database, especially as they seek to better engage their customers. Researchers can also plan on additional questions to mine these intra-household interactions by asking in detail about household composition. Our experiment attempted to screen for renters who were responsible for paying their own utility bills, however there may have been some who had financial support from parents and guardians without them actually being listed as the ratepayer; this could be resolved by making some changes to the questions asked in our survey instruments.

This was also a relatively small sample size in terms of utility-scale pilots, but this was reasonable given the modest budget and scope of the project. Fortunately, thousands of observations from the smart meters and in-home displays add statistical strength to our analysis. In some experiments 200 households is a reasonably large social science experiment, but when working in the field and attempting to quantify something elusive as behavior change, there should be more support from utilities and technology providers to deploy innovative pilots at a large scale. Indeed, without support from the partner utility, which was in turn supported by regulators calling for more research in this area, the field experiment would not be possible. While there are complex, large scale projects that have been completed and take advantage of quasi-experimental designs (e.g., Allcott (2011)), this paper makes a valuable contribution by focusing directly on a hard-to-serve population and represents a small-but-important early step towards understanding the role that smart meters and associated enabling technologies can play in new efficiency programs.

2.5 Conclusions

This paper documents the results of an experiment that attempted to examine energy-related impacts from the interactions between two commonly-examined aspects of behavior-based demand side management in the energy industry: feedback and incentives. With advances in technology that enable the so-called smart grid, it is now becoming possible for utilities to offer time-based rates to their customers that more accurately reflect the true price of energy at a given moment. Through smart meters, it is now possible to provide real-time feedback through in-home displays and other enabling technologies. As these technologies and services have emerged, organizations like the DOE and national laboratories have developed standards and protocols to accurately measure the impacts of interventions aligned with these technologies. Blending theory with current practice, it is now possible to build on these recommended approaches to measure the interactions between feedback and incentives through rigorous experiments. Our experiment attempted to look carefully at the renter population in one Vermont service territory with a high proportion of renters, a class of home occupant that needs to be better-served due to classic market failures in the efficiency industry like split-incentive problems.

While this experiment had a relatively small sample size, the results suggest that renters who typically do not make large capital investments in their homes due to split-incentive problems can contribute to energy efficiency resources through behavior changes alone; that is, the interventions and methods in our experiment could be used to measure savings that may not have been previously available to claim savings in efficiency programs. However, if the results are to be extended to current practice of deploying broadly new rates to residential customers without knowing whether they are renters or homeowners, there may be risks. Using time-based rates and other new policies in this population without adequate information feedback resources could cause energy consumption to increase. On the other hand, investing in feedback interventions like IHDs, without comprehensive engagement strategies to motivate usage of the feedback tools (like financial incentives to save energy), may result in lower performance and the so-called mean-time-to-kitchen-drawer effect.

Certainly, more work is needed in this area. Researchers, utilities, and policy makers should consider how best to examine specific populations like renters; future experiments could again focus on renters and also investigate the influence of other characteristics such as households that include low-income, multifamily, elderly, or special-needs individuals, and located in urban, suburban, or rural communities. These will be easier to investigate as standards and protocols, such as consistent survey instruments, continue to emerge and be refined. For example, these groups can work to support and encourage robust research designs and work with product makers to offer adequate funding for equipment and opportunities to bring down costs. There is also a need to more fully embrace social scientists in energy studies, with a careful eye towards the human aspects of these programs such as how users experience the feedback, their preferred mode of communication (e.g. mobile app, text message, email, or physical display), and their knowledge and perceptions of energy use as it may affect the usefulness of these devices. As the technologies that provide feedback continue to mature, there will be more opportunities to investigate how different levels of feedback–such as appliance-level real-time feedback–may complement the whole-home feedback provided in this experiment. While it may be premature to assume the outcome of this experiment translates precisely across broader populations, these results highlight the need to continue deeper explorations between the intereaction of various demand side management interventions, including feedback and incentives, in residential populations that are known to be more than homeowners, the typical targets of efficiency programs. The main findings presented in this paper, that feedback combined with financial incentives had significantly stronger and longer-lasting energy savings outcomes than either of the two interventions separately, should highlight a few important lessons for those in the energy industry. First, while we should be wary of solutions that offer only new technologies without adequate reasons to engage with the technology, we should not eliminate these interventions when they fail to succeed; rather, we should investigate how to make their support more meaningful to the user and why the intervention may have failed. Second, we should recognize that, in some populations, rate-based interventions that provide some financial incentive may fall flat alone without proper support mechanisms; rate designers could consider the target population of these rates and what supporting technologies are now available as the smart grid and other internet-enablished smart devices come to the market. Third, this domain of research should continue to explore interactions between interventions in sub-populations of residential energy consumers, like renters, using mixed methods that draw from rigorous experimental designs and social science.

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Paper 2

Is it in your head? The influence of real-time feedback and incentives on perceptions of energy

Expected publication: PNAS

Abstract

Public perceptions of household appliance energy consumption have been demonstrated to be skewed; people generally underestimate the actual demand of many common household energy appliances, hampering individuals' ability to effectively influence their personal energy consumption. Proponents of the smart grid assert that with better information, especially feedback closer to the time of actual consumption, residential energy consumers will act with greater efficiency, finding opportunities to conserve energy and save money. However, renters may behave differently than owners. This is partly because of the reality of durable good purchases make the decision points, at least relative to the point of purchase, few. They are also unable to realize these savings even when provided real-time information feedback because of a split-incentive problem: renters are not motivated to invest in more efficient products because they cannot realize the long-term savings due to their tenure in the property, and the property owner is not motivated to invest in efficiency because the tenant pays for electricity and they'd receive no savings benefits. Given this problem, and the potential impact this may have on energy conservation and efficiency programs, it is unclear if better information through real-time feedback will change perceptions of home energy use or motivate residents to curtail energy consumption by sacrificing comfort alone. Here we describe aspects of a field experiment in which residential renter households were randomly provided real-time feedback through in-home displays (IHDs) and given performance-based incentives to reduce consumption; they were also surveyed about energy perceptions before and after treatment. Compared to a control group, all treated households demonstrate statistically significant changes in perceptions of energy consumption, but the specific changes in individual appliance perceptions vary across treatment groups, suggesting that those given feedback were able to more accurately understand the impacts of specific appliances on their overall energy consumption. This finding suggests that feedback works to align perceptions and, when focused on a particular task by an incentive, may perform more predictably, having an impact on future programs to alleviate split-incentive problems in renter households.

3.1 Introduction

As technology continues to evolve at a dizzying pace, we don't often take time to consider how it helps or hinders our understanding of the basic features of modern life. For example, it is unclear how new technologies in the energy sector affect our knowledge and perceptions about energy and, consequently, our actions or overall behaviors. In this context, the emerging internet of things (IoT) has begun to play a role in the modern power grid, often called the smart grid. When it comes to local and national power systems, IoT and the smart grid bridges both personal and public domains: the individual choices and actions we make in our homes and workplaces in turn influence the broader system through the energy we require to meet our everyday needs. Previous work has examined the influence of these technologies on end-use energy consumption through field experiments that measure changes household energy conumption to varying degrees of success and rigor (Karlin et al., 2015b). This line of work has yielded promising evidence that suggests varying levels of information feedback are associated with increased energy conservation or savings through behavior change (Ehrhardt-Martinez et al., 2010; Foster & Mazur-Stommen, 2012; Karlin et al., 2015b). At this point, however, it is still unclear *why* these behaviors are changing. Other research has shown there are gaps in perceptions of energy use (Attari et al., 2010). Thus, an important step to unpack how feedback influences energy-related behavior changes is to understand how perceptions of energy use change when additional feedback is present. When given feedback about energy consumption, do perceptions of appliance energy consumption improve and change? Does feedback–additional information about specific energy decisions–help better understand and prioritize which pro-environmental behaviors have the most impact? Similarly, financial incentives can be a means to draw attention to certain behaviors. Can incentives lead to changes in home energy consumption, delivered through a competitive rebate incentive, influence individuals in the same or different ways?

Bruekers and Mourik (2013) describe energy-related behaviors broadly as intentional or habitual, but

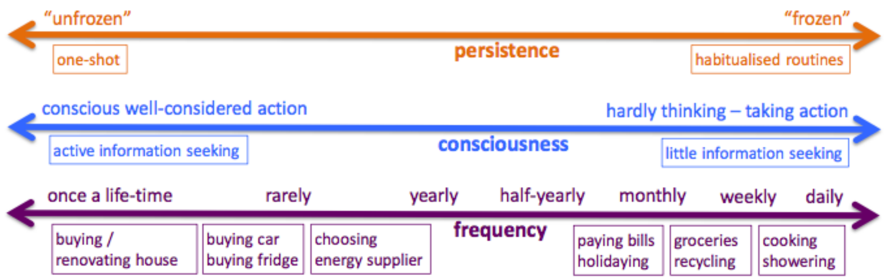

Figure 22: Behavior spectrum from Breukers & Mourik (2013). Efficiency programs commonly target behaviors on the left side with rebates, incentives, and education materials, but newer behavioral efficiency programs (and this dissertation) attempt to influence behaviors and habits on the right side.

further explain them on a spectrum spanning persistence, consciousness, and frequency (see Figure 22). While not directly stating this in their goals, traditional efficiency programs have historically focused on one-shot, infrequent actions that occur closer to the left side of this spectrum, such as motivating purchase of the most efficiency appliance or home; that being said, each appliance likely falls at different points on this spectrum based on profiles of use, frequency, and–potentially, discussed in this paper–perceptions of actual energy consumption. The true uncharted territory in behavior-based energy efficiency is related to the more frequent, harder-to-change unconscious habits and routines. More research is needed to understand which mechanisms cause behaviors and their associated energy consumption to change; this paper seeks to contribute in this area by exploring how perceptions of certain appliances vary and change when presented with two interacting interventions. We describes results from a field experiment in which renter households were provided real-time feedback on home energy consumption through in-home displays (IHDs), a set of financial incentives to conserve energy, or both. In addition to these interventions, participating households were surveyed about their perceptions several typical household items' energy use before and after treatment.

3.2 Methods

This section describes the steps taken to (1) record individual perceptions of energy use before and after treatment and (2) quantify these changes by treatment period and treatment group.

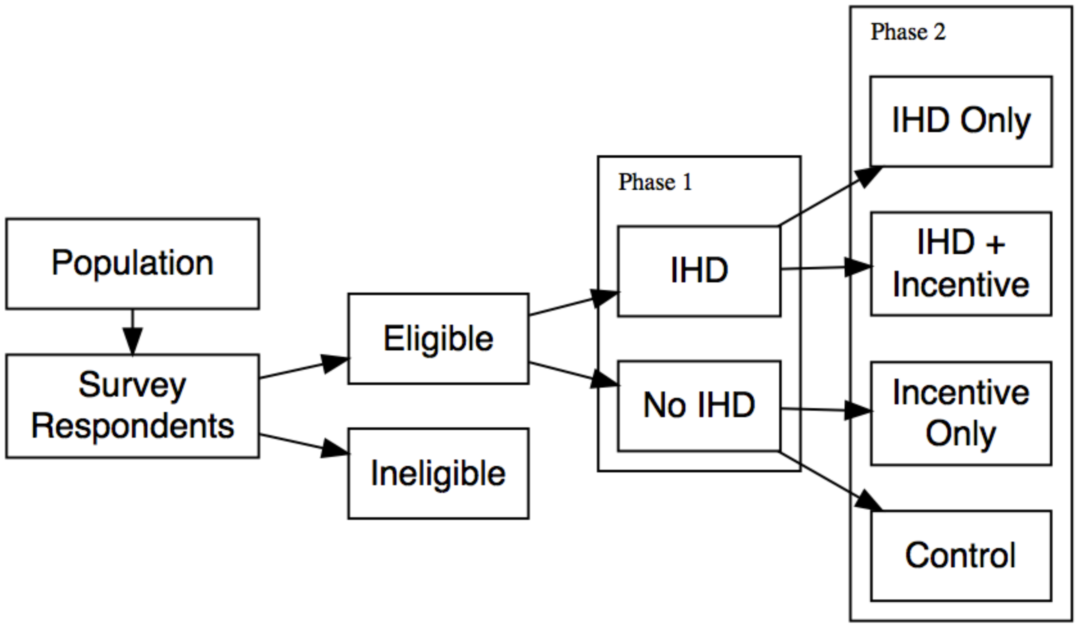

Figure 23: Respondents were randomly selected into treatment groups in two phases, ultimately ending up as one of four treatments.

3.2.1 Participants and Recruitment.

Potential subjects were drawn from a population of 7,738 active undergraduate, graduate, medical, and continuing education students at the University of Vermont who were confirmed by the university to be living in off-campus campus housing not managed by the university. The university was unable to provide with great accuracy the total number of households this population comprised, but estimates from student support organizations on campus suggest the average household size was 2-3 people. Using this value we can estimate approximately 3,000 homes in the full population. We used a survey instrument delivered to this population as a recruitment and screening tool; for

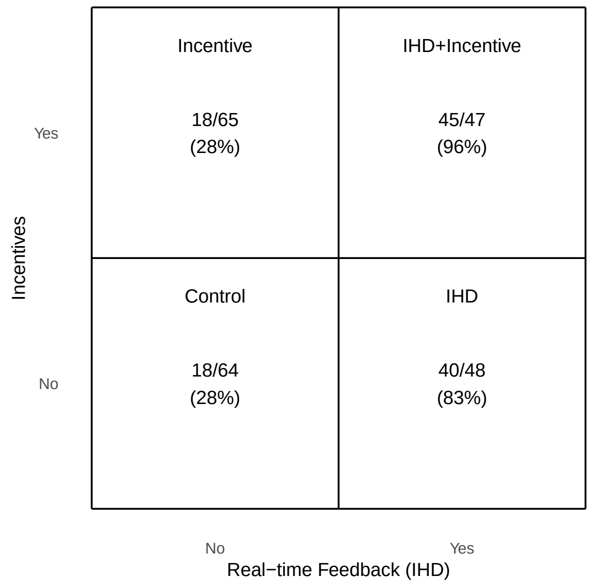

Figure 24: Response Counts by Treatment Group. Groups receiving IHDs had higher response rates in the post-treatment survey.

expedience, the instrument also included pre-treatment survey questions based on those used in Attari et al. (2010). 224 subjects were recruited from rental households in Burlington, Vermont to participate in a field experiment testing the interactive effects of real-time energy feedback (delivered via IHDs) and incentives on residential energy consumption. Fredman et al. (n.d.-a) describes in detail the energy impacts of this experiment. Figure 23 illustrates how respondents eligible for the full experiment were screened into the experiment as subjects and assigned to groups. The experiment consisted of two phases: first, IHDs were configured and provided to randomly-selected homes and then after a few months the second phase began, in which incentives were delivered.

Subjects were recruited through a campaign using email invitations, email reminders, and public outreach requesting completion of a screening survey[1] that took place in from late August to early October of 2015. Building on a previous experiment that tested methods to increase survey participation, respondents were incentivized to participate using a regret lottery with social pressure (Todd, 2010). Potential survey respondents were informed they had been entered in a prize drawing and, if they completed the survey and their name was drawn, they would earn $100 both for them-

[1](The instrument is described in Appendix A: Survey Instruments)

selves and a friend of their choice. Survey respondents were also informed that should their name be drawn and they had not completed the survey, they would win nothing. They were also informed that their chances of winning were increased by having others complete the survey and list them as a friend to win the other $100 "buddy prize." This method of increasing response rates draws from evidence that social pressure can motivate charitable giving (DellaVigna et al., 2009) and voter turnout (Gerber et al., 2008). The survey was open to responses for approximately eight weeks and had a 10% response rate (N = 772).

The screening survey included questions that recorded housing characteristics and respondent tenure in the household as well as customer details to facilitate matching households with utility data (e.g., address and utility ratepayer name, which were later removed from the dataset to ensure subject privacy) and to screen for eligibility for the any treatment in the study (internet access, smartphone/tablet ownership, and interest in using a device to display real-time information). The experimental population of households were all Burlington residents and granted permission to the utility via the survey to share smart meter data on energy consumption, and had the baseline eligibility prerequisites to recieve an IHD. To offset a selection bias (Heckman, 1979) where subjects may have only been interested in experiencing this new technology, subjects selected to receive an IHD were offered $50 at the end of the study period after returning the device. This substantial financial compensation was considered enough to attract subjects who would otherwise be disinterested in using an IHD and was confirmed in post-experiment conversations with subjects after they returned their IHDs.

For this analysis, 121 (54%) unique respondents had both pre- and post-treatment survey responses out of the 224 that were screened into the experiment. Figure 24 describes the breakdown of subjects in the experiment by treatment group showing who responded both pre/post treatment. Each box represents one of four treatments; the first number is those who completed both pre- and post-treatment surveys, the second value is the total number in the group, and the percentage value in parentheses is the proportion of the group to have complete survey data. 121 out of 224(54%) subjects completed post-treatment survey. While there were subjects who did not respond after the treatment period ended, there was a reasonable balance between the groups although there are more complete responses from the groups that received the IHD, likely due to the extra $50 compensation. All groups were notified there would be a prize drawing and could not receive cash rewards unless the survey was completed. The Incentive group subjects were told they could have won anywhere from $5-120 based on their performance in the study.

3.2.2 Survey Instrument

The surveys was administered online using LimeSurvey (LimeSurvey Project Team, 2012). The complete screening survey and post-experiment survey are available as supplemental information.[2] With the exception of screening questions for eligibility, the pre- and post-experimental surveys included questions that recorded subjects' current attitudes, beliefs, perceptions, and future intentions about home energy use and conservation behaviors based on recommendations from previous experimental and theoretical work (Abrahamse & Steg, 2011; Allcott & Mullainathan, 2010; Attari et al., 2010; Karlin et al., 2015a, 2015b; Todd et al., 2012). A set of questions were specifically based on survey materials from Attari et al. (2010) to assess how perceptions of household appliance energy use changed before and after the field experiment. The results of the survey are explored more deeply in Palchak et al. (Palchak et al., n.d.). We build specifically on the work of Attari et al. (2010) by asking questions about perceptions of appliance energy use both before and after administering the experimental treatment; previous work only looked at perceptions in one moment in time, not before and after an intervention. We ask respondents to estimate how many units of energy 11 different devices or appliances (a CFL, an LED light, a laptop computer, a smartphone or tablet charger, an electric clothes dryer, a portable space heater, a room air-conditioner, a central air conditioner, a dishwasher, a standard refrigerator, a hair dryer) typically use in one hour. To

[2]See appendices

help respondents make these comparisions, we provide an example that a standard incandescent light bulb uses 100 units of energy in one hour. As a randomized controlled trial (RCT), assuming pre-treatment responses are similar, any significant variation in changes may be attributed to the treatments.

3.2.3 Analysis

Attari et al. (2010) use multi-level models to derive per-subject "perception curves" that reveal how average perceptions of appliance energy consumption varies by appliance as well as a slope and intercept for each household's perception curve. Figure 25 depicts the results of this previous analysis, showing that public perceptions of energy are skewed. This implies that suboptimal decisions are made by individuals when it comes to choosing the best behaviors to change that result in the most conserved energy because the relative impact of those changes are ill-perceived.

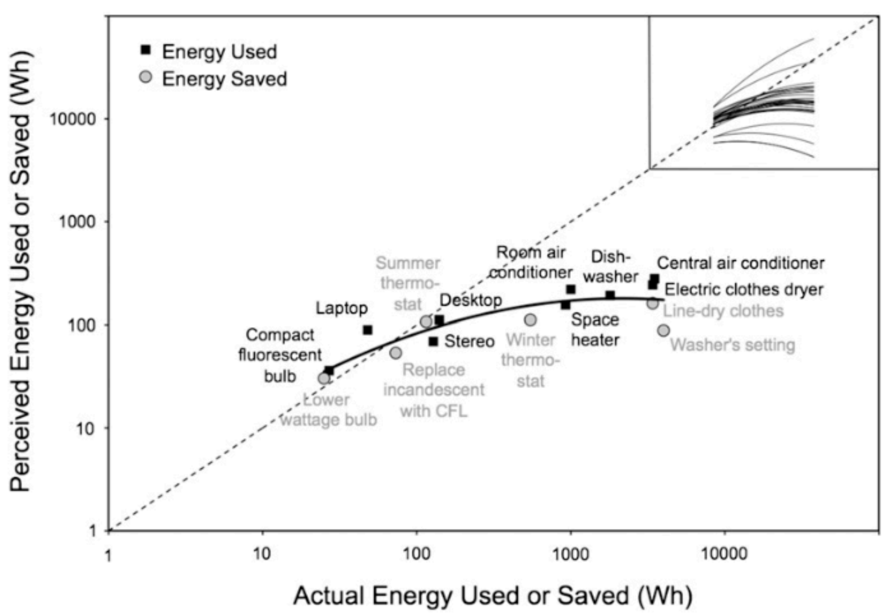

Figure 25: Average perception curve, from Attari et al., showing that appliances using more energy are generally more under-estimated (Attari et al., 2010). Dotted line represents "perfect" perception of energy used or saved. Inset is a representative sample of per-respondent perception curves.

Building on this work, we reproduce the method in Attari et al. by constructing these curves from both pre- and post-experiment survey responses and then compares the changes between experimental treatment groups. This reveals how well the groups who received feedback improve their perception curves, suggesting that these groups may have learned more about their energy consumption because of exposure to these devices. The model outputs for each treatment group and pre/post survey period can then be aggregated and visualized similarly to Figure 25.

In Attari et al 2010 (2010), perceptions of energy were modeled with considerations of respondent numeracy (a question asked in their survey). We did not ask questions about specific energy savings perceptions; the results of the above paper and subsequent discussions revealed that these were not as necessary to assess energy perceptions (Attari, DeKay, Davidson, & Bruin, 2011; Frederick, Meyer, & Mochon, 2011). We also added (e.g., mobile device charger) and removed (e.g., desktop computer) a few appliances in the survey question to reflect changes in conventional use since the original survey.

Like Attari et al., we model the relationship between actual appliance usage and respondent perceptions using the formula:

$$\log_{10} Perception_{ij} = \beta_{0j} + \beta_{1j} \log 10 Actual_i + \beta_{2j}(\log_{10} Actual_i)^2 + r_{ij} \tag{1}$$

where i is the device or activity and j is the participant. The coefficients β_{0j} and β_{1j} are treated as random effects and vary about their average values (the model fixed effect), thereby allowing each participant to have his or her own regression equation (i.e., participant j's intercept and slope will differ from the average intercept and slope). Like Attari et al., the quadratic effect is fixed and not allowed to vary so β_{2j} was the same for all participants. We also center the values of $\log_{10} Perception$ and $\log_{10} Actual$ relative to the original mean of $\log_{10} Actual$ so coefficients can be more easily-interpretted. In equation (1), the intercept β_{0j} indicates over- or under-estimation, the slope β_{1j} indicates the general relationship between perceptions and actual values, and the coefficient for the quadratic term β_{2j} indicates the curvature in that relationship, although it does not change for each participant. This provides detailed assessment of the accuracy of individual perceptions; if the respondent had perfect perceptions, then $\beta_{0j} = 0$, $\beta_{1j} = 1$, and $\beta_{2j} = 0$. In addition to this previous work, we calculate individual t-tests comparing mean $log10(kWh)$ for each appliance in each treatment group to elucidate whether individual appliance perceptions are changing within the underlying model parameters. We also describe the distribution of random effects before and after treatment for each group, testing for significant differences between these effects. Extending this work, we add levels to these models to account for pre- and post-treatment periods as well as treatment groups. Using the model outputs for each treatment and period, we test for differences before and after treatment within each group, and compare those differences. This helps answer the central question of this paper: do the experimental interventions change perceptions of appliance energy consumption, and do they vary by treatment group?

3.3 Results

We used R and RStudio for general analysis and the package `lme4` to perform the linear multi-level analysis of the relationship between perceived and actual perceptions by treatment group and survey period (Bates, Mächler, Bolker, & Walker, 2015; R Core Team, 2017; RStudio Team, 2016). Visual inspection of residual plots did not reveal any obvious deviations from homoscedasticity or normality. P-values for the multi-level models were obtained by likelihood ratio tests of the full model with the effect in question against the model without the effect in question. For simplicity of comparison to the model described in Attari et al., we used the same model specifications; future work could explore other iterations and models to potentially obtain and test for a more precise fit.

We first replicated relevant elements of Attari et al. (Attari et al., 2010). Using each respondents' estimated energy used by 11 devices, with the energy used by a 100-W incandescent light bulb in 1 hour provided as a reference point, we assessed the correlation between these perceptions and actual energy use values after transforming all values with base-10 logarithms to reduce positive skew. The mean correlation between $log_{10}Perception$ and $log_{10}Actual$ was r = 0.55 [t(1505) = 25.31, P < 0.0001, η^2 = 0.298], indicating that our participants also had imperfect knowledge of which devices used greater amounts of energy, perhaps moreso than the previous research. In the post-treatment survey, mean correlation between $log_{10}Perception$ and $log_{10}Actual$ was r = 0.6 [t(1505) = 29.19, P < 0.0001, η^2 = 0.36], suggesting there were improvements in perceptions.

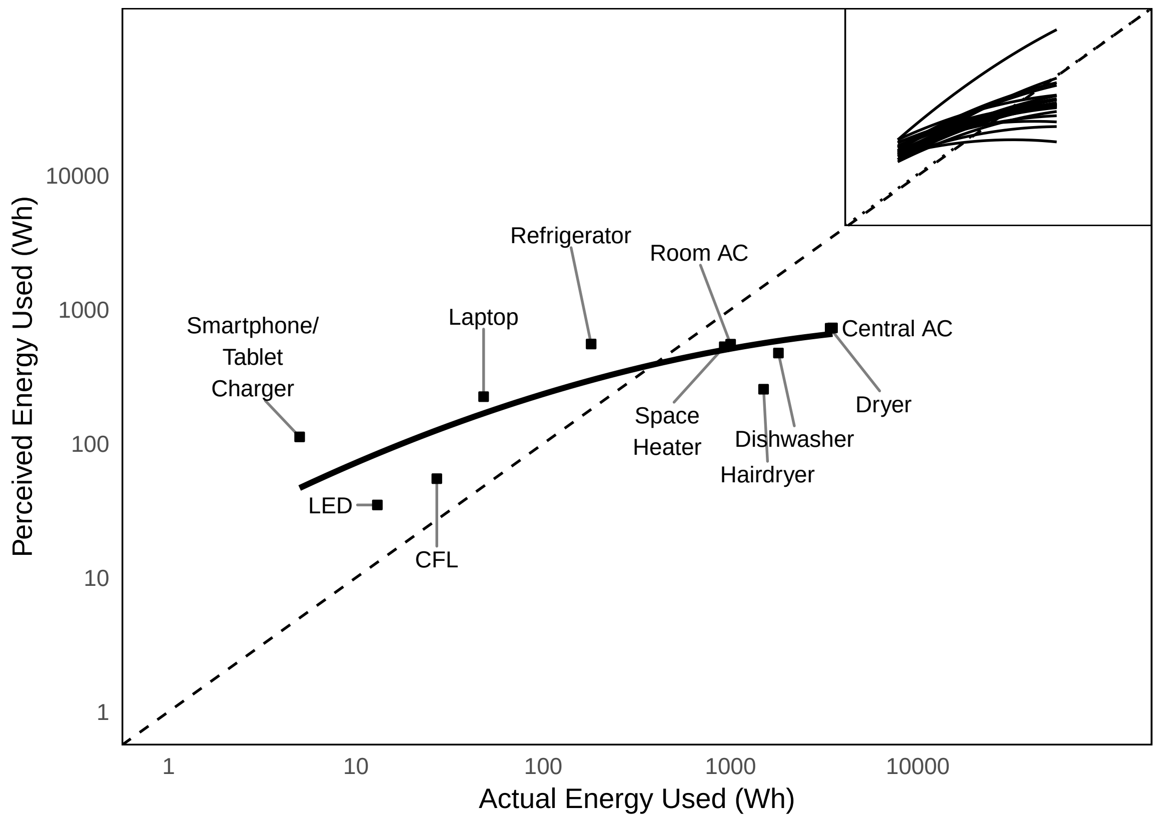

Figure 26: Replication of Attari et al. figure depicting mean perceptions of energy used a function of actual energy used for 11 devices. 95% confidence interval bands in the figure are omitted for clairty (and are typically no larger than the symbols). Diagonal dashed line references what would be perfect perception. Inset: Individual regression curves for a sampling of 30 respondents. While curvature of the regression is similar to the figure in Attari et al. (Attari et al., 2010), respondents generally are over-estimating smaller applianaces more but still under-estimating larger appliances prior to any treatment.

Again replicating Attari et al., we used the multilevel regression model from equation (1) to more deeply examine these relationships. Figure 26 is a replication of Figure 25 using our experiment's responses and also includes an inset of 30 randomly-selected individual perception curves. The average intercept in the pre-treatment survey, which gives the average elevation of perceptions at the mean of $log_{10}Actual$, was significantly positive [M(β_{0j}) = 0.04, t(180) = 1.3, P < 0.0001]. On average, based on the methods in Attari et al. our participants overestimated energy use by a factor of $10^{0.04} = 1.1$. The average intercept in the post-treatment survey was significantly positive [M(β_{0j}) = 0.07, t(180) = 2.23, P < 0.0001]. Using post-treatment survey responses, respondents on average overestimated energy use by a factor of $10^{0.07} = 1.19$.

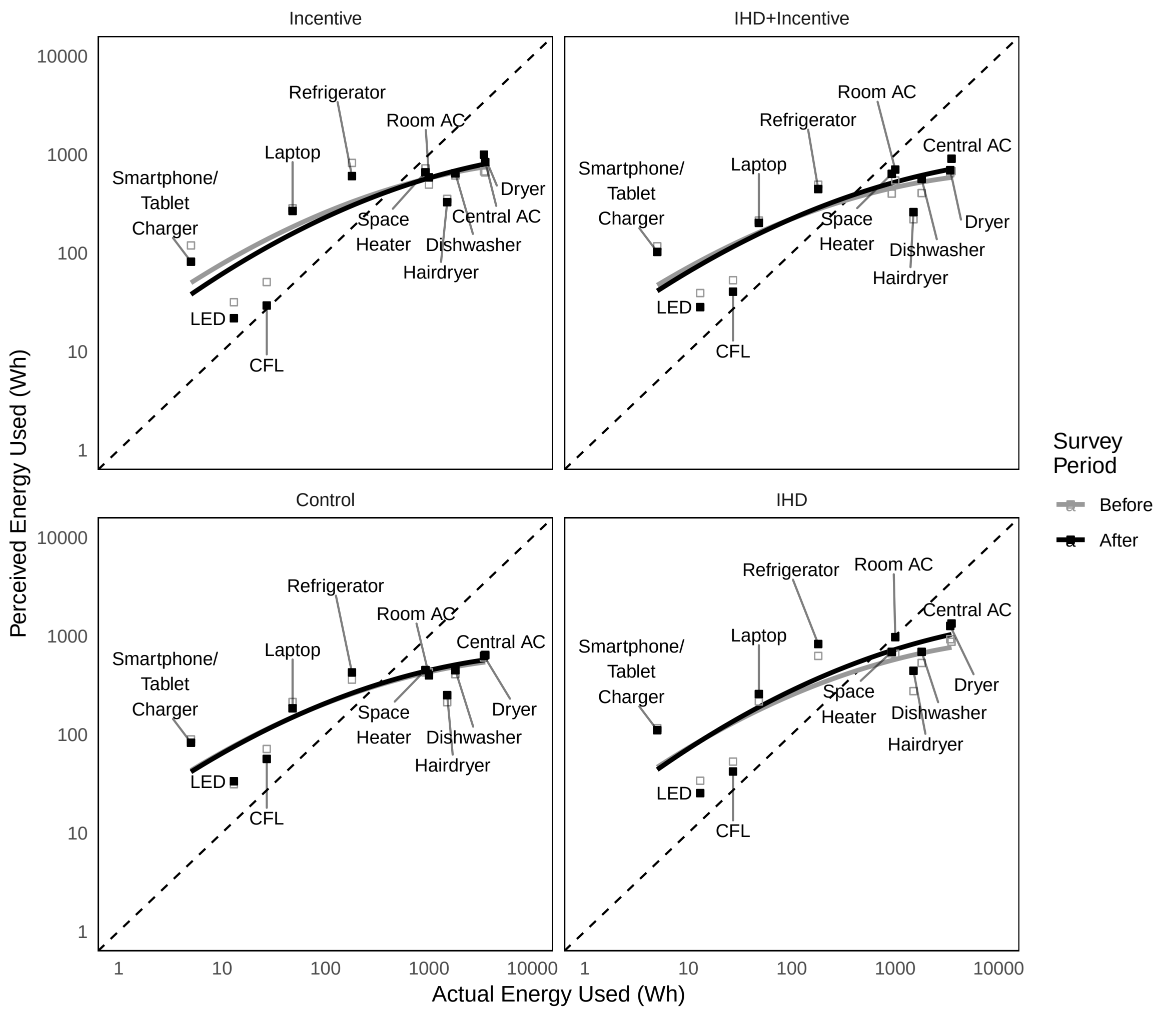

Figure 27: Multilevel model results by treatment group and survey period, indicating how the groups receiving feedback improved perceptions at the high end of the appliance energy spectrum, while groups receiving incentives changed on the low end; the interactive group changed on both ends.

Table 5: Mean random effects by treatment group and period. There was no significant change in elevation (intercept) for each model, but each treatment group experienced changes in their model slope, indicating improved perceptions.

Group	Model Term	Pre-treatment	Post-treatment	Difference	t
Control	Elevation	-0.027 (±0.051)	-0.017 (±0.047)	0.01	0.208
Control	Slope	0.315 (±0.025)	0.328 (±0.026)	0.013	0.776
IHD	Elevation	0.081 (±0.048)	0.157 (±0.037)	0.076	1.642
IHD	Slope	0.355 (±0.022)	0.41 (±0.018)	0.055*	2.496
Incentive	Elevation	0.088 (±0.057)	0.064 (±0.063)	-0.023	-0.336
Incentive	Slope	0.341 (±0.028)	0.393 (±0.028)	0.052*	2.530
IHD+Incentive	Elevation	0.007 (±0.04)	0.039 (±0.051)	0.032	0.672
IHD+Incentive	Slope	0.312 (±0.018)	0.363 (±0.02)	0.051*	2.572

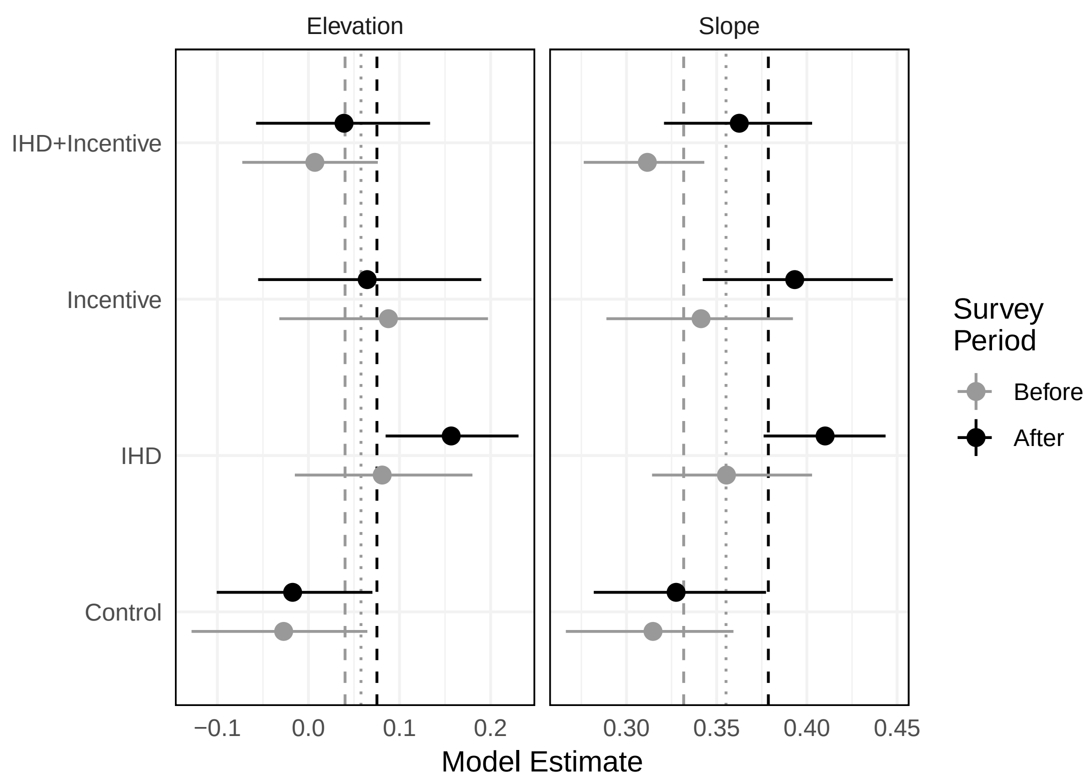

Figure 28: Mean random effects for each treatment group and survey period. Dotted line represents full model fixed effects for intercept (elevation) and β_0 (slope), while the dashed lines represent model averages for each survey period. The slopes for the groups receiving feedback appear to have changed the most significantly.

Adding to this line of research, we can compare the differences between the each treatment group before and after treatment was applied. In Fredman et al. (n.d.-a), there was a significant savings effect for the IHD-only group in phase 1 but this effect stopped in phase 2. In phase 2, the combined treatment group demonstrated significant energy savings while the incentive-only group showed no savings and potentially had negative savings (albeit non-significant statistically), suggesting that the incentive "backfired." Table 5, Figure 27, and Figure 28 describe the differences between each treatment group for each survey period and t-test results with 95% confidence intervals. These figures helps visualize the changing perceptions overall and the table helps quantify these changes. There was no significant change in the elevations of each treatment group between periods, but the treated groups did have significant changes in their slopes while the control group did not. The IHD, Incentive, and IHD+Incentive groups all saw significant changes in modeled slopes between the pre- and post-treatment. The difference in slopes ranged from approximately a factor of $10^{.05}$=1.12 to a factor of $10^{0.06}$=1.1481536.

A surprising outcome was what happened when new appliances were added, extending Attari et al.'s work. For example, we asked about small smartphone/tablet chargers (also called "wall warts"), as these are now pervasive in most homes. As visible in Figure 27, there was an outsized under-estimation of this particular device (which typically draws about 5w of power) and the average response in the entire population pre-treatment was an average of 178Wh, a nearly 40-fold overestimation of energy use. While the result of the models do not change drastically when these values are removed, the bend the curve becomes more skewed; given that it did not alter the model results drastically, we keep these data in the model. While this individual appliance difference at the low end of the spectrum is not of primary relevance to the central question of this paper, it is noteworthy that one of the more modern devices in our survey instrument–a smartphone charger–is so significantly over-estimated; on its own it tells a story of how the rise of smartphones and tablets, while meeting many of the needs served by desktop and laptop computers, uses considerably less energy.

3.4 Discussion

These results suggest that these interventions - real-time feedback on energy consumption and/or financial incentives to focus on altering household energy consumption - may contribute to improvements in individual perceptions of appliance energy usage. However, each treatment does so in subtle yet importantly different ways. The IHD group had the most pronounced shift, especially with respect to perceptions of the more energy-intensive household items. The incentive treatment also produced a shift towards better perceptions, but upon visual inspection these shifts occured mostly around mid- to low-range energy items. While there is always some expectation that an interactive treatment could produce hybrid results, the combined treatment produced changes in perceptions that reflect a combination of the two - perceptions of appliances became more accurate overall in both high- and low-energy items. While the energy savings associated with the treatments are discussed in detail elsewhere (in the first article of this dissertation), the combined treatment was found to demonstrate the largest and potentially most persistent changes in energy use during the course of the experiment (Fredman et al., n.d.-a). Given this, it is plausible that these results indicate a connection between perceptions of energy use and actual energy use; an individual gaining a better understanding of how much energy is used by a certain action may lead to a better priorization of behavior changes that have a higher impact energy consumption. The additional improved perception of additional energy impact brought on by large household appliances may influence the individual's motivations and behaviors around using those items. For example, the incentive-only group may have had no additional information to understand the outsize impact of laundry machines relative to lightbulbs, so actions with lower energy impact may have been taken, and greater attention was paid to these low-impact devices. Given the market for energy efficiency in this service area with a focus on lighting efficiency, the respondents could have had easy access to this information, whereas the groups that had feedback could understand which appliances were driving up their energy use and chose to act upon this new knowledge. Considering the group that has both treatments, this could explain how there are greater energy savings in results described in Fredman et al. (Fredman et al., n.d.-a). Reflecting on the theoretical concepts displayed in the behavior spectrum in Figure 22, perceptions could be considered a third dimension: the behavior changed could also be a function of the accuracy of perception to the impact of that behavior. For example, if the perception of a behavior was more accurate, it may attenuate or amplify the frequency, consciousness, or persistence of a particular behavior.

There were some limitations to this research and several opportunities for improvement. There was clearly an imbalance in survey response rates for treatment groups, which affected the sample sizes of each group and potentially influenced model results. Future researchers should work to correct these imbalances, perhaps by offering similar survey completion incentives to all treatment groups to ensure higher response rates. It is also unclear as to whether each of these appliances is actually present in the participant homes that had feedback; it was assumed that many of these appliances are probably present, and the lack of actual feedback on the devices could contribute to discrepancies in perceived energy use. Future technology may be able to automatically detect the present of such appliances, or survey questions could include this when asking about energy perceptions.

3.5 Conclusions

Wynes and Nicholas recently found that actions likely to have the most impact on anthropogenic climate change are largely misunderstood by the general public and not included in textbooks (2017). With concern over climate change at an all-time high (Leiserowitz et al., 2017), this suggests that when it comes to making decisions about which behaviors have the greatest impact on energy consumption and climate change, people lack the information to make the most impactful or efficient decisions. Simultaneously, utilities vary in how they prioritize customer engagement, reach statewide clean energy goals, and avoid the so-called “utility death spiral” (Stephens, Kopin, Wilson, & Peterson, 2017). Offering utility customers different rates and services to help them save money and energy, theoretically, would help improve customer satisfaction, retain those customers, and help all participants in the electrical grid improve environmental quality. Theories attempt to explain the gaps between knowledge and action around pro-environmental behaviors, often describing a complex interaction of external factors (e.g. economic situation, political and social factors, or infrastructure), internal factors (e.g. personality traits, value systems, or knowledge), and existing barriers (like old behavior patterns) (Kollmuss & Agyeman, 2002). Renters, even morseo than homeowners, have additional challenges to identify means to save energy, due to, for example, split-incentive problems with landlords and difficulties understanding how to best save costs related to household energy consumption. Search the internet for "how to save energy" and one may find hundreds of energy literacy campaigns focused on the "low hanging fruit" of energy efficiency actions like changing lightbulbs and unplugging devices when not in use. Yet Wynes and Nicholas point out certain home energy behaviors like changing light bulbs to low-energy LEDs pale in comparison to the climate benefits of eliminating driving or having fewer children, while changes in other more substantial household behaviors, like reducing the number of laundry loads per week, can substantially contribute to energy efficiency and conservation outcomes (if we knew which behaviors to prioritize). Specifically in this energy domain, Attari et al. previously found that individual perceptions of energy use were generally skewed; these "perception curves" indicated that energy consumed by high-power household items (such as central air conditioners or laundry dryers) were underestimated (Attari et al., 2010).

This paper confirms and extends this previous work by Attari et al., further suggesting that this method is generally reproducible and can be used to determine the extent to which individual perceptions of household appliance energy consumption are skewed; by way of our study population in this experiment, we also confirm that this skewing occurs in renter households speficifcally as well as the general population surveyed in Attari et al. Given our finding that these perceptions continue to be skewed, it stands to reason that future literacy programs should focus on changing changing and realigning those perceptions; real-time feedback may help identify which appliances draw the most power and consequently are more appropriate targets for behavior change than, say, changing lighting behavior. We also describe results from pre- and post-treatment survey questions about perceptions of household item energy use, which was asked as part of a broader field experiment testing the interactive effects of real-time feedback and financial incentives to change energy consumption in rental households. In this experiment, we find that after each intervention, whether separate or interacting, significant changes in perception relative to the control group occur. Upon closer inspection, the groups that received feedback appear to change perceptions more at higher energy-using appliances than lower appliances while the groups that received the incentive experience more changes at the lower end of the energy-consuming spectrum. The interactive treatment, combining real-time feedback and incentives, experienced changes at both ends. In the context of results from the broader experiment, in which more savings occured in homes with feedback and moreso the ones that received incentives as well, this suggest that the combination of interventions may, through the incentive, drive action while through the feedback, build awareness of which actions have the most substantial impact.

This entire contribution enriches our understanding of behavior-based energy efficiency by deploying pre-post surveys to better understand changes in energy literacy and consumption (Karlin et al., 2015a). We provide further evidence that a blended approach to research in energy studies can be advantageous, something called for in the literature (Sovacool, 2014a). Our results, while imperfect, begin to draw more clear connections between the behavioral mechanisms that drive quantifiable energy changes and the role that enabling technolgies related to the smart grid can be deployed to engage and motivate more efficienct behaviors. This work offers a potential strategy made available by the internet of things and the smart grid–time-based rates supported by real-time feedback–to rapidly achieve vital climate goals and is especially relevant as efficiency programs focused on lighting approach their twilight, given they have successfully transformed markets to eliminate high-energy incandescents (York et al., 2015). As such, policy makers should consider how improving tools and interventions to help people more accurately perceive individual device energy use or their environmental impacts could scale up to larger measurable impacts on the power grid.

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Paper 3

Not so fast: The nuanced benefits and risks of real-time feedback, incentives, and demand response in rental households

Not So Fast: The Nuanced Benefits and Risks of Real-time Feedback, Incentives, and Demand Response in Rental Households

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ABSTRACT

Smart grid proponents (and vendors) are quick to tout new products and services that provide real-time energy use feedback to customers. These advocates assume that better and more information leads to more efficient customer behaviors. Others see these technologies as a pathway to reach the underserved. For example, renters caught in a split-incentive problem might be unable to participate in traditional efficiency programs, so real-time feedback with demand response (DR) messaging can support those customers' participation. However, this is no simple solution and is fraught with risk for customers, efficiency program managers, and utility decision makers. We discuss results from a randomized controlled trial (RCT), in one utility service territory with smart meters, testing interactions between incentives and feedback on renters: (1) real-time feedback alone might work, albeit temporarily, making it difficult to justify technology costs to achieve long-term savings; (2) feedback combined with behavior-based incentives potentially double the savings benefit of feedback alone, and last longer; (3) incentives alone—whether as a rate structure or competitive game—might not work or it might backfire, adding to renters' energy burdens; and (4) the source of these additional savings might be related to better aligning users' perception of appliance energy consumption with reality. Taken together, there are benefits and risks. Utilities might see potential for strategic load growth and DR benefits and efficiency programs might benefit from coupling feedback with compelling messages, but there is a risk of increasing costs to customers if smart grid programs are not designed and carried out carefully to engage customers.

Introduction

Everyone in the modern world, whether they are aware of it or not, participate in the energy system – albeit differently – and their interactions are increasingly intertwined as our society is connected through internet and communication technologies (ICT). Consider the following stakeholders in these scenarios: (1) regulators task a utility to develop new time-of-use rates that support improvements in demand side management and distributed energy resources; (2) a portfolio manager at an efficiency program needs to deliver new sources of measurable savings, perhaps from behavior change, since existing incentive programs (say, an LED lighting program) have successfully transformed the market and are projected to shrink as a source of future savings; and (3) renters living in an apartment want to save money on electricity bills, but can't make any changes to their home's energy efficiency because the landlord won't allow it or pay for it (a classical split-incentive problem). These three scenarios relate to the future of residential electricity consumption. Power system infrastructure will continue to change, whether in response to the impacts of climate change or from proactive policies to better serve customers who now demand more service. It will therefore be important to understand the nuanced benefits and risks that come with new technologies and policies relating to the smart grid.

There are more than 65 million installed smart meters nationwide (covering approximately 50 percent of all households). That number is expected to reach 90 million and possibly 1 billion worldwide (Cooper 2016; Mooney 2015; Uribe-Pérez et al. 2016). We might expect the three previously-mentioned scenarios to emerge as service areas continue to expand their use of smart meters. They can support distributed energy sources, storage, and more precise rate structures (not to mention more precise efficiency program measurement and evaluation). Thus, it will be important for regulators, utilities, and program designers to consider how their decisions might affect residential energy consumers. The energy efficiency industry often discusses energy burdens yet it does not as frequently consider the changing housing market, which could have a subtle, profound effect on residential energy efficiency savings potential. Behavior-based efficiency programs can offer a method for reaching renters, whereas traditional programs will struggle to overcome market barriers and failures.

Renters and Energy Efficiency

Programs that encourage greater energy efficiency in multifamily residential buildings have varying degrees of success (Philbrick et al. 2014a; Pivo 2014). For example, programs in Vermont and Illinois offer instant rebates to subsidize the cost of light bulbs or home energy audits, making it easier for residents to access these services (Robinson 2014). This does, however, require the occupants to invest time and / or money to reduced energy consumption objectives. Occupants, whether renters or owners, might have different motivations for participation that could override any rational decision about a financial incentive. Further, barriers such as competing priorities of work and family might prevent the resident from acting on these incentives. There are also differences in how homeowners and renters consume energy; for example, owner-occupied units consume more total energy than renter-occupied units, but renter-occupied units consumer more energy per square foot (Carliner 2013). This suggests that homeowners gravitate toward living in larger homes, whereas renters lack the capacity or ability to be more efficient. Quite simply: renters consume energy differently than homeowners.

The "American Dream" of owning a home and perhaps some land is changing as people shift where and how they live; these shifts constitute a looming threat to the national energy efficiency landscape. The worldwide urban population is now over 50 percent; as of 2010, 80.7 percent of the U.S. population live in urban areas. The preference for homeownership over renting is also changing. Figure 1 shows how homeownership populations have changed in the last three decades. A recent MacArthur Foundation study found a persistent, strong desire for home ownership, but most of the renter and homeowner respondents believed that buying had become less appealing while renting had become more appealing. This shift, the study showed, related to perceptions about the economy (e.g., the housing crisis) and lifestyle changes; current renters and homeowners both believed that that renters can be as successful as homeowners. Nevertheless, across all social and political demographics, there was a strong desire for safe, affordable, and stable housing, in any form (Hart Research Associates 2013). Harvard University's Joint Center for Housing Studies (JCHS) indicated that 37 percent of American households were renters in 2015, up from 31 percent in 2004, marking this decade as the largest recorded period of growth in the renter population. These rates have stabilized to about 36 percent in 2017. Both the Hart and JCHS studies show how the population of renters is growing against that of homeowners. Given the increases in carbon emissions, residential sector energy efficiency is becoming increasingly important to, regardless of ownership status. However, energy policy and housing policy often do not address renters' needs—and even less so, those of low-income renters, who disproportionately bear the costs of energy use relative to wealthier renters. Low-income renters are less likely to have energy efficient appliances in their homes (Davis 2012).

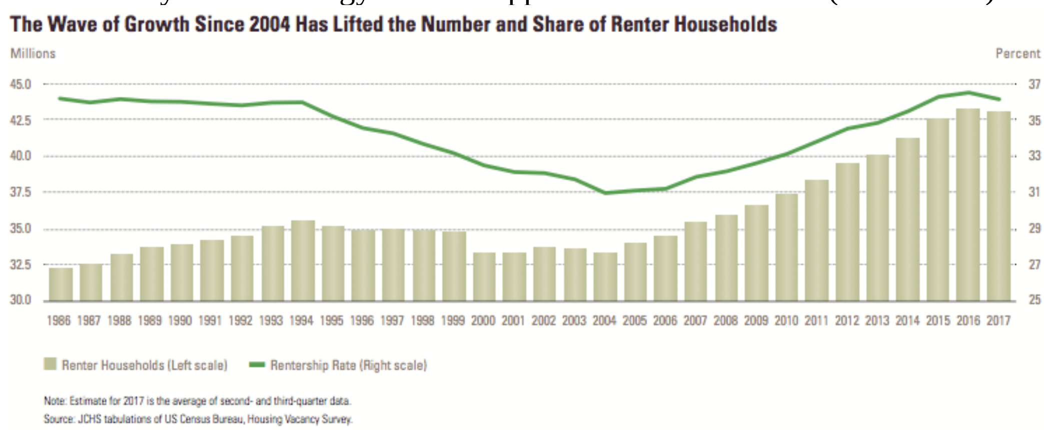

Figure 1 Changing patterns of homeownership since 1986. *Source*: Joint Center for Housing Studies of Harvard University.

Affordable and stable energy costs in the home would make housing—rental housing in particular—more affordable and efficient (Philbrick et al. 2014b). Thus, increasing the energy efficiency of homes would make energy costs more predictable, if not lower. Gillingham and Palmer (2014) describe an "energy efficiency gap" in which consumers purchase energy-efficient products at a slower than optimal rate. They also explain how market failures and behavioral factors contribute to this gap. The "split-incentive" problem, one such failure, occurs when—in the case of rental properties—landlords' and tenants' interests do not align, resulting in no purchase of the most energy-efficient product. A property owner might be responsible for appliance or equipment choices, whereas the resident is responsible for paying for the electricity they consume. Owners thus have no incentive to upgrade to more efficient appliances because they do not see cost savings; residents might never recoup the cost savings of a more efficient appliance while they live in the unit, so no one purchases the appliance (Carliner 2013). The lack of policy interventions results in rental properties' being avoided by energy efficiency programs (Robinson 2014). Given the swelling of the rental population, the viability of energy efficiency practices that rely on residential investments are at risk.

Interviews with utility operators and other stakeholders (Buckley et al. 2014) and with an efficiency service operator (Robinson 2014), and sampled literature (Carliner 2013; Gillingham and Palmer 2014) have indicated better information would lead to better decision making on split incentives. Better information could include rating and labeling programs—such as ENERGY STAR®. It could also involve novel efforts to require information about utility costs being made publicly available and benchmarked (Cox et al. 2013). Carliner (2013) notes that an effort to bring benchmarking and disclosure of energy expenses in rental housing is under way; this could help renters choose where to live. But there are difficulties with this. In Chicago, for example, politicians played up the drama by referring to benchmarking as "public shaming" (Wernau 2013).

Behavior-Based Efficiency and Renters

While we do not examine the role of shame, we do address other behavior-based (BB) strategies like real-time feedback and time-based rates. These BB programs typically involve outreach, education, competition, rewards, feedback, and benchmarking (Sussman and Chikumbo 2016; Todd et al. 2012). Recent research suggests that vulnerable populations (elderly, low-income, and chronically ill households) might respond differently from average households, yet more research into specific populations is needed (Cappers et al. 2016). Research on energy feedback and time-of-use rates continues to grow, but it is not yet known whether renters respond to energy feedback the same way that homeowners do.

Long-standing research investigating the energy savings potential of behavior changes in homes suffers from levels of satisficing. These studies have adapted to complexities and constraints of expense, timing, sample sizes, utility customer populations, treatment methods, and analysis approaches (to name a few). New protocols have helped standardize the research and measurement of energy impacts of BB efficiency programs, data collection, and modeling recommendations, which are based on insights from earlier work (Stewart and Todd 2015). As more researchers rely on these protocols, and as the protocols evolve, we can expect more rigorous insights. There are thorough reviews and meta-analyses of utility-run BB program evaluations across hundreds of service territories, such as those by Mazur-Stommen and Farley (2013). Experimental evidence from many of these intervention methods (Darby 2006; Ehrhardt-Martinez et al. 2010; Fischer 2008; Karlin, Zinger, et al. 2015; Vine et al. 2013; Vine and Jones 2016) suggest that BB programs can cost-effectively deliver average energy savings of 4 to 12 percent; estimates significantly higher than the average often reflect less robust research designs (Delmas et al. 2013). When household real-time feedback was used in previous experiments, savings averaged closer to 9 percent (Ehrhardt-Martinez et al. 2010; Foster and Mazur-Stommen 2012; Karlin, Zinger, et al. 2015; York et al. 2015). Real-time feedback is associated with behavior-based changes in energy consumption, but the consistency and accuracy of a predictable, quantifiable change remains somewhat elusive. Given the nature of existing research, the emerging standards for reaching robust results, and the relative uncertainty of the role renters could play in DSM, we investigated this further, partnering with a medium-sized urban municipal utility in Vermont with smart meters and a substantial renter population. The resulting complex field experiment became, in the language of social system transitions, a bounded socio-technical experiment (Brown and Vergragt 2008).

A Field Experiment

Through this partnership, we randomly gave renters (university students living off campus) either (1) real-time feedback from tabletop in-home displays (or IHDs, a digital picture frame with an energy dashboard) that included both mobile and web apps, or (2) incentives that mimic modern time-based rates and conservation incentives, or both. We also had a control group. In the research design phase, we determined a process that would satisfy the utility's privacy policies for sharing data from advanced metering infrastructure (AMI, or smart meters), serve a policy application for the utility (such as testing possible rate designs or technologies), and simultaneously meet research goals. We did not want to explore different *types* of feedback (such as those described in Karlin et al. 2013) and thus worked with the utility to identify a third-party provider that offered diverse feedback mechanisms. Thus, participants could choose their preferred feedback method, whether a tabletop display, a web portal, or mobile app. The regulatory structure did not permit the creation of temporary rates, so we improvised by creating an incentive structure modeled on peak-time rebates (Faruqui et al. 2012), using behavioral insights to create a socially competitive game-like reward system (Vine and Jones 2016). The incentive (instructions with conditions to "win" money) had two components, delivered via e-mail: (1) we asked participants to do their best to conserve energy every day, and any household reducing its daily energy consumption below a pre-treatment personalized baseline would receive at least $5 per month, up to the full value of the electricity bill, depending on their relative savings ranked in the group; and (2) we told participants that they would randomly receive an e-mail 24 hours in advance of a "peak event," in which they would be asked to reduce their energy consumption during set hours, and that, if they did this better than the rest of the group, they would win $20, effectively simulating a peak-time rebate. To recruit participants efficiently, maximize potential research insights, and satisfy privacy concerns, we created a survey instrument that screened for renters with persistent in-home Wi-Fi, access to a mobile device, and a willingness to share utility data while also collecting pre-treatment data. A post-treatment survey assessed certain changes over the study period, repeating certain pre-treatment questions, to illuminate how subjects experienced the treatments. The study population ranged from juniors and seniors through graduate / medical school, and all said they were responsible for paying their utility bills.

The experimental design builds on the work of Karlin, Zinger, et al. (2015), Karlin, Ford, et al. (2015), Karlin et al. (2017) and the Uniform Methods Project's Residential Behavior Protocol (Stewart and Todd 2015) by using an RCT recording energy use from smart meters over time *and* uses pre- and post-treatment qualitative data. The energy analysis provided interesting results regarding savings (see Fredman et al.

(n.d.-a) for details). The results of the pre- and post-treatment surveys, specifically regarding changes in perceptions of energy, based on the work of Attari et al. (2010) described in Fredman et al.(n.d.-b). Palchak et al. (n.d.) discusses the outcomes of in-depth interviews and other pre- and post-survey responses.

We intend with this paper to spark a conversation with the energy efficiency industry about the risks and benefits of new technologies and policies on a growing rental population in an era of evolving power systems. We hope to move beyond answering, "Did the interventions work?" toward unpacking the question, "What does this mean in practice, accepting that the results were significant and meaningful?" This might help energy efficiency practitioners relate the experimental outcomes to energy programs that use feedback and / or some form of financial incentive to change patterns of consumption (time-of-use rates, peak-time rebates, or other similar demand response mechanisms). If the experimental results indicate a broader phenomenon, we might consider how to design programs that produce the most desirable outcomes from the perspective of each of the scenarios' stakeholder types.

Surprising Results?

The experiment ran from late August 2015 to early May 2016. The Residential Behavior UMP (Stewart and Todd 2015) recommends at least a year of data for adequate analysis, but the timing of the academic year makes it difficult to follow households consistently for a full year, but also reveals an issue about renters with limited tenure. With a data sharing agreement in place from each participating household, we collected historical and ongoing AMI data (15-minute intervals) until the experiment concluded, when most leases ended in 2016. Although some households had data going back to three years (AMI came online between 2012-2013 for most of this service area), these data were consistently available from August 2015 through May 2016. We excluded households that had a significant disruption of service in this period (for example, a move-out). The timing of recruitment and randomization lent itself well to a phased treatment approach in which we deployed IHDs first (Phase 1) and later deployed the incentive treatment (Phase 2), so that Phase 1 can be understood as a simple RCT comparing feedback to a control group, and Phase 2 is a two-way RCT looking at interactive effects. Comparing Phase 1 and Phase 2 results provides insights into how responses to real-time feedback changes might be influenced by incentives. To analyze treatment effects, we closely followed the UMP (Stewart and Todd 2015), using a time- and household-fixed effects difference-in-differences (DiD) regression model. Recruitment began in September 2015 and we obtained participant AMI data in October after we closed the screening survey. We set up IHDs in early December and in subsequent waves in mid-December and mid-January.

The results in Table 1 suggest Phase 1 participants who received real-time feedback had 8.4 percent difference-in-difference daily energy savings ($p<0.1$). The results suggest that these renters could make changes in energy consumption during this period; further, the information plausibly aligns with previous research about real-time electricity feedback (Ehrhardt-Martinez et al. 2010).

We randomly selected half of the participants in the Phase 1 IHD group to receive the incentive treatment. We distributed the incentives equally between each of the two deployment waves. Similarly, we chose half of the Phase 1 control group for the Phase 2 incentive-only group. Like Phase 1, we specified a fixed-effects regression model for Phase 2, but also accounted for the interactions between each treatment, such that each DiD model coefficient demonstrated average DiD for each of the three treatment groups relative to the pre-treatment period control group (Table 1). In this phase, the IHD-only group had a (statistically non-significant) 5.7 percent increase in daily energy consumption ($p > 0.1$), although the IHD incentive group experienced 16 percent savings ($p < 0.05$). The group that received only the incentive treatment showed a (statistically non-significant) 8.4 percent increase in energy consumption ($p > 0.1$). Figure 2 (left side) visualizes the DiD between the treatment groups.

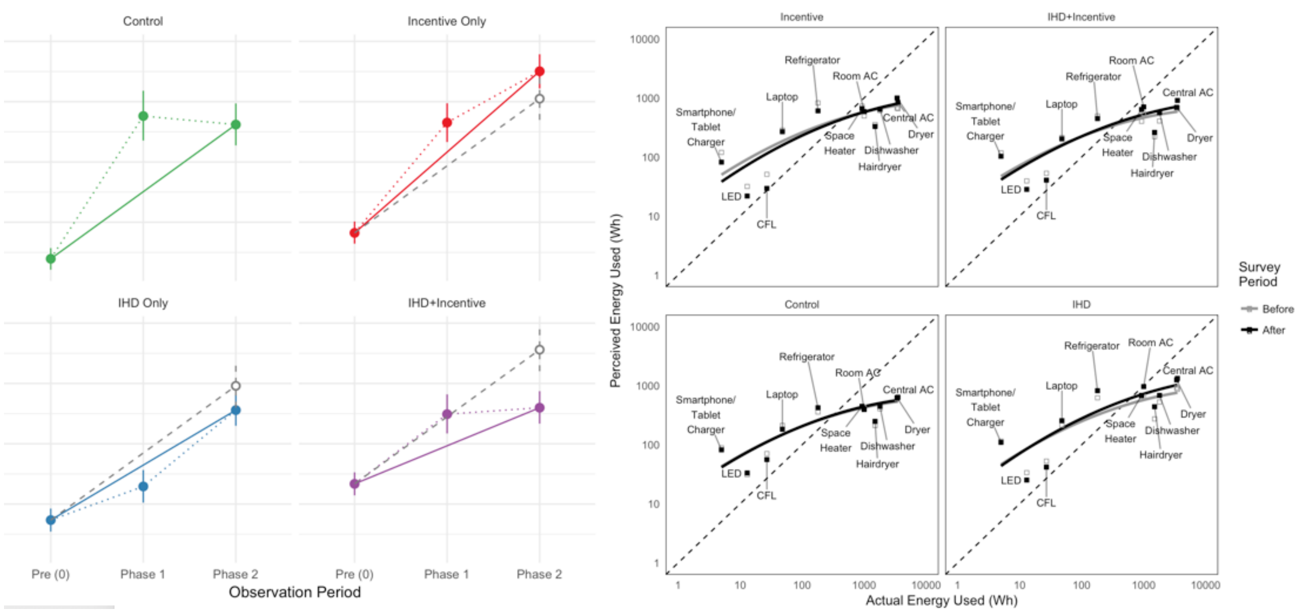

Figure 2. Left side, gray dashed line: Expected-treatment results had the group behaved identically to the control group. Dotted line: Slope of change between phases. Right side, pre- and post-treatment survey responses to the question, “If an incandescent lightbulb uses 100 units of energy in 1 hour, how many units of energy do the following appliances use in one hour?” Both axes are log-10 scaled, where the dashed line represents perfect perception. Changes in regions of small and large appliances tend to vary across treatment groups.

Moving on from simply quantifying changes in energy consumption, we used our pre- and post-treatment survey data to examine *why* consumption might be changing as a result of the treatment. There were 126 participants who responded to both pre- and post-treatment surveys, out of the 239 total participants (that is, 53 percent completed both surveys). Attari et al. (2010) described a method for measuring how public perceptions of appliance energy consumption can be skewed from actual values. In our experiment, we reproduced Attari et al.’s method (survey questions about household appliance energy consumption) and repeated it in the post-treatment survey. We expected to see whether perceptions changed after participants were exposed to one or both of our treatments.

Figure 2 (right side) shows the changes in perceptions of appliance energy use across all treatment groups. In this analysis, we found that both feedback and incentives can alter perceptions of energy, but do so differently. Groups showed significant changes in perceptions after treatment, whereas the control group did not. But the groups that received feedback experienced perception changes mostly in more energy-consuming devices.

Table 1. Regression model results

Group	Phase 1	Phase 2
IHD only	-0.0894*	0.0567
	(-0.049)	(-0.0545)
Incentive only		0.0841
		(-0.0582)
IHD + incentive		-0.1674**
		(-0.0718)
Number of observations	26,400	28,479
R^2 (full model)	0.7182	0.75
R^2 (projected model)	0.0031	0.0044
Adjusted R^2 (full model)	0.7147	0.747
Adjusted R^2 (projected model)	-0.0093	-0.0075
** p < 0.05, * p < 0.1		

Discussion

It was initially affirming to see the group who received energy feedback demonstrate savings, a result seen elsewhere (for example, in Karlin, Zinger, et al. [2015]). It was also understandable to see those savings wane over time in the second treatment phase (the "mean time to kitchen drawer" effect). When the combined-treatment group doubled their savings at the same time, however, this appears to confirm previous theories discussed in Karlin et al. (2013): Feedback technology might give users the ability to learn or diagnose certain aspects of their energy consumption, but the incentive could sharpen their attention on a task that the feedback helps support (for example, identifying the largest energy loads). In this sense, the combined treatment's altered perceptions of larger appliance energy consumption could confirm this. Alone, it is surprising to see a fairly "standard" economic message ("We will pay you, if you do X") effectively backfire. This suggests that standard neo-classical economics is limited in this context, and that the perverse incentive response might be due to the split-incentive problems. That is, without information, renters feel powerless to make changes and might do the wrong things, without an effective way to understand the consequences.

Based on this, deploying time-based rates or large-scale demand response programs without sufficient decision support tools, or giving customers a stronger locus of control, could create more harm than good unless a utility is simply hoping to increase rate-based revenue. We gave a segment of the experimental group receiving real-time feedback an incentive to alter their energy consumption, rewarding them for conserving energy across time, or for successfully participating in simulated demand response events. The savings in this group effectively doubled, compared to the savings achieved in the previous period. However, the segment of this treatment group that did not receive the incentive did not show savings in this second period, suggesting that the effectiveness of feedback alone wanes over time. Studies of general residential populations show this same phenomenon (for example, Houde et al. (2013); Schleich et al. (2017)). Taken together, the benefits and risks depend upon the role played in a behavior program. Utilities might see potential for strategic load growth and DR benefits, whereas efficiency programs might benefit by combining feedback with engaging and compelling messages or incentives. The primary risk to customers, if these incentives do not involve training or information-based support systems, is the likelihood of increasing overall costs. Like Attari et al. (2010), we found that customers often underestimate the actual energy consumption of larger appliances, but we showed that better information could improve these perceptions. Further, we found that in trying to win money, customers used their improved knowledge to achieve more effective behavior changes. This finding relates to recent research from Wynes and Nicholas (2017); when people fail to accurately perceive the effects of certain actions (whether appliance energy consumption or larger actions that have larger climate impacts), they might be wasting their efforts on less-efficient actions (such as reducing lighting use, rather than reducing air conditioning or perhaps eliminating the use of motor vehicles).

Conclusions

These results present an interesting line of discourse. They suggest we need to deepen our discussion on whether new technologies or DSM programs help or hurt populations that are not typical single-family owned homes—such as those who have low, fixed incomes or inflexible schedules due to socio-economic status or health. The clearest response today is, “It depends,” and thus, we need more research. Our summary here of the experimental results add to the research on real-time feedback and incentives. But in this case, we examine the experience of energy utility customers residing only in rental properties. When given tools to understand their household energy use in real time, renters in this randomized controlled trial experienced noticeable savings, measured through a differences-in-differences fixed-effects model. But the results suggest that attention to feedback wanes over time, and incentives might sufficiently interact with feedback to influence the extent and persistence of savings, perhaps through the alignment of perception to reality.

We need research to understand how best to measure persistence in behavior-based efficiency programs. However, we need even more research to understand how and why renters respond differently. The results from this experiment show that new rates requiring attention to time-based rates or time-critical behaviors should always be coupled with decision support technology. Failure to do so likely increases energy cost burdens, especially for vulnerable populations. Renters constitute a large portion of the residential population, and they should be considered in future program designs, especially because they encounter split-incentive problems that most homeowners do not. As regulators begin to require additional efficiency resources from behavior change, we must consider all possible tools, especially as a lighting cliff approaches.

Feedback alone might not provide a persistent source of savings, and time-of-use rates may negatively affect utility customers who are often the most energy burdened. Curiously, using the two tactics together could result in more effective savings. Our results suggest that more sustainable behavior-based energy efficiency programs will be those that couple new technology with carefully crafted engagement mechanisms. This highlights the need for diverse services and offerings from every utility. We do not have evidence that a "one size fits all" approach will work, unless an evaluation of research in a particular market or service area indicates otherwise. As with previous experiments and pilots using feedback, there is certainly potential for behavior-based efficiency savings in renter households. However, these programs might be more successful and sustainable when they are complemented by engaging programs that leverage behavioral insights.

Our results suggest that finding an ideal financial incentive can be a challenge, given that households that did not receive real-time feedback potentially saw a relative increase in energy use. However, promising strategies that balance people's needs and behaviors with appropriate technology will likely create a path to more successful energy efficiency and demand response programs.

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Conclusions and Future Work

This dissertation started from a personal curiosity–based on earlier work experiences practicing sustainability and climate action planning on a college campus–about how behavior-based changes might be measured as accurately as the investments in capital infrastructure to achieve energy and climate goals. On a personal level, I wanted to better understand how people and technology are interacting in new ways and how this could influence the future of society. Ultimately what resulted–an approach to analyze the experimental data in two parts followed by an interpretation of the results for the energy efficiency industry–has produced what the reader hopefully sees as an example of science done well and meaningful contributions to the the sectors that operate in the sociotechnical energy landscape. Whether or not the outcomes of the experiment described in this dissertation were "successful" in terms of what they sought to do (reduce and/or shift energy consumption) these results can better inform future decision-making by utilities, consumers, and regulators when it comes to evolving the electric power system. Additionally, this dissertation provides more examples of statistically valid insights into how technologies that deliver real-time energy feedback and potential new behavior-based electric efficiency programs can support changes in consumers (or not); it also describes some of the risks present when relying too much on technology alone or deploying new rates without adequate decision support tools.

A clear lesson from this experience is that while investment in the smart grid has been important, it is not nearly done yet, even in areas where the infrastructure build-out may be complete. We need the smart grid to support distributed energy resources like solar, wind, and storage; these are necessary energy resources to continue work towards environmental sustainability and adequately respond to climate change for human survival. Additionally, the smart grid is also important for players in the utility industry to better serve and support their customers by improving relevant decision support and locus of control (e.g., choosing appropriate rates or responding to those rates at times of high price or grid impact) as well as create stronger platforms for customer engagement.

Given the tensions discovered in discourse around customer engagement in various utilities around the country, making support services easier and more effectively will likely be a net win for service providers (Stephens et al., 2017). However, a main takeaway has been that while these technologies are promising, if misused, they could unintentionally harm certain populations by making energy costs increase; at the same time, if used wisely, the new technologies and rates made possible by investment in the smart grid could greatly benefit these same populations by enhancing their personal knowledge of household energy, identify efficiency opportunities, and bring down energy costs. The renter population will likely continue to grow; utilities and other players in the demand side management (DSM) landscape ignore this at their own peril. “Split-incentive problems” and other market failures around efficient products are real and could become a bigger issue as time of use rates come online. There are likely many more opportunities for DSM, but they must be integrated and carefully designed. This has been my experience in practice at VEIC as the industry tries to find new, compelling ways to reach customers through innovative programs and services.

The most important message for the industry: be careful when it comes to time-based rates. New rates and technologies are going to bring opportunities that benefit and stabilize the grid as more distributed energy resources come online. However, new rates are risky without supporting technology and yet, that technology will likely fall flat without solid engagement strategies and compelling reasons for customers to engage with these new products and services and should thus be considered intertwined. Much like the wearable devices that are purported to bring improvements in personal health which do not work simply by wearing it, the benefits of smart meters is not that they are installed in homes, it is that they are designed to be used to its fullest by the home’s occupant and the utility program managers.

It is not solely the responsibility of wise and benevolent utility managers to make the smart grid a success, although it is their responsibility to keep the grid in their territory online and serving electricity to customers. Regulators can and should put support systems in place before new rates come out, such as requiring careful design and testing of rates in collaboration with researchers despite the slow and deliberate nature of this work. Utilities should also facilitate this process, and work with regulators and experts to solve their data issues; this is the new reality as the internet of things (IoT) comes online and releases a deluge of data. This includes addressing various data structure and privacy issues by collaborating with third parties whose interest is more than keeping the lights on–non-profits and standards bodies whose mission may be to serve certain populations or address data interoperability can provide frameworks to allow for consistent analysis and data sharing. Those of us in the industry work better together when we protect and serve the ratepayer, which coincidentally, is also nearly everyone who lives in a home and consumes electricity. A clear next step is for utilities to improve how they manage their customer data. Smart meters bring an added layer of complexity because, when utilities collect 15-minute interval data, one customer's annual data changes from 12 monthly data points per year to over 35,000 data points, nearly a 3000-fold increase. This can be an IT challenge, but it is fairly useless without context, and this requires better information about customers, so utilities can improve how they collect and manage data about *the people* they serve rather than just the electricity they sell. In my experiences working with utilities in Vermont, improving this data is not an easy feat and should, hopefully, be supported by regulators as it is a benefit to ratepayers and the state's clean energy goals. Ultimately, it will be a waste of resources if the smart grid isn't fully realized and it becomes a vast sea of underutilized data occaisionally used to manage power outtages and a means to eliminate human meter readers.

The makers of grid-connected technologies should take note of these findings as well. Those actors in the IoT space should work to future-proof their products and services, despite being an incredibly challenging feat. By carefully engaging in user-centered design exercises, they can better understand what the customer wants. In our research, we found that users did not find the IHD appealing and failed to adequately interact with the supporting apps on a regular basis. This was likely due to how the data was presented, and that participants anecdotally reported an overload of screens in their lives; perhaps a sign of things to come. In the future, it seems that dynamic web and mobile apps and technologies that are able to leverage the new audio-based technolgies could survive hardware problems. At VEIC, we are working with a next-generation hardware provider who anticipates a time when users ask a smart speak to report how much energy their home is using and to recommend ways to bring down their energy costs. Ultimately, it is really best when researchers and various industry, utility, and policymakers work together.

As discussed in the previous three papers, there were some limitations to this research. With approximately 250 homes in our experiment, we had a small sample size relative to many studies in the energy industry, but our sample was larger than many studies in the social sciences.
Our survey instrument and approach had some issues. For example, we had to eliminate respondents who did not complete their post survey and some homes with IHDs did not have adequate connectivity, making it a challenge to find a signal in the noise of our data. However, making our experimental design as rigorous as possible helped mitigate these issues and AMI data at the scale mentioned previously also strengthened the validity of results. Essentially, experiments like this need to be repeated and coordinated across service areas to identify a truly valid result, so we can collectively tell a more complete story through our combined research insights. The outcome from paper two is an especially promising example, in that we could repeat the method and find similar results while augmenting the method to measure changes in perception. The experiment's population was intended to be renters, but due to constraints of the funding, the population was primarily student renters; not every renter is a student and thus introduces issues about external validity. We also asked questions about whether or not the ratepayer was the study participant, a roommate, or a parent/guardian, in the hopes of discovering whether college students were paying their own way or being supported by parents. While we learned that the vast majority did not have parents as ratepayers, we failed to ascertain if the parents were contributing to the students' finances. This highlights an important question to ask in future research. Despite this, the findings are relevant to many other service areas that include college-aged rental populations. Given the expansive population of millenials around the world and the current trajectory of homeownership, many of

these individuals in college now will be future renters and remain an important population to study further. With renters, timing and seasonality will always be a challenge. The DOE recommends at least twelve months for a complete experimental period, but we were limited to a school year due to logistics and the reality that student renters are transient. This does highlight the benefit of fixed effects regression models to absorb unknown features of time, but requires rigorous experimental designs that may be harder for utilities to implement.

There are some broadly useful results from the entire dissertation. Renters, based on quantifiable behavior changes from interventions using behavior and incentives, are reachable by efficiency programs, and more should be done to explore how to reach this and similar populations. Programs like this are nascent in the industry, but the so-called "platinum standard" that blends social science with technological interventions may be a way to bring these underserved energy consumers more efficiency services. It is vitally important that rigorous, carefully designed experiments continue to explore this intersection and inform energy policy and utility services. The smart grid does bring value to this population and should be considered an important component in the future of utility-customer relations. However, this is a mixed statement; time-of-use rates enabled by the smart grid might hurt populations like renters without an adequate decision support system, but those support systems are also enabled by the smart grid. In summary, this dissertation highlights that, despite various fits and starts, the smart grid is a net benefit. We are seeing benefits continue to emerge, but they need to be more carefully deployed, with an eye towards serving the cusomters–the people–at the heart of the power system. As the saying goes, what can't be measured can't be managed; the smart grid, just like the various wearable health devices and new IoT widgets coming online every day, give us new tools to measure, manage, and become more mindful of our decisions so we can have a more sustainable future.

Thank you for taking the time to read this dissertation.

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Appendices

A Survey Instrument

A.1 Pre-treatment Survey

Instructions

Please fill out this form to sign up for the UVM Off-campus Home Energy Study.

Your responses will enable us to **verify your eligibility** for the study. It should take less than 15 minutes to complete. All responses are kept confidential and personal information will be removed at the end of the study.

To go backward or forward in the form, use the "Previous" and "Next" buttons at the bottom of the screen. **Do not use your web browser's back or forward buttons.**

Please read these details carefully.

This is a study on household energy use. You will be asked to grant permission to share your household's energy data from your electricity meter with the researchers. No other information about your account will be shared. If you are not authorized to make decisions about your home's electricity account (for example, the bill is in your roommate's name), you will need to get permission from that person.

When you complete this form, **you will be entered in a prize drawing**. If your name is drawn, you and a UVM friend of your choosing will each receive **$100**. Ask your friends to also complete the form and designate you as their prize partner - this will increase your odds of winning!

If you are eligible and selected, you may be asked to participate in some easy activities to earn **rewards.** You may also be provided a device to see your home electricity use. All groups can earn compensation for their participation - from **$20** to **$250**.

This research is conducted by doctoral students in the UVM Rubenstein School of Environment & Natural Resources affiliated with the Gund Institute for Ecological Economics and the UVM Smart Grid IGERT. The study is supported by the UVM Clean Energy Fund.

To begin the form, click "Next" below.

There are 50 questions in this survey

Study Eligibility

This section contains questions to assess your eligibility for participation in the full study.

[]What is your relationship to the University of Vermont? *

Please choose **only one** of the following:

- Undergraduate Student
- Graduate Student
- Medical Student
- Faculty/Staff
- Alumni
- Living with a current UVM student
- No relationship to UVM
- Other:

Choose the answer you identify with the most. For example, if you are a full-time staff and also take graduate courses, choose Faculty/Staff.

Do you live off-campus? * (y/n)

Do you rent or own your home (your local residence)? *

Do you have wireless internet in your home? *

Do you have access to an iOS or Android smartphone or tablet? *

Who is listed as the account holder on your electric utility bill?*

Please choose **only one** of the following:

- I am listed as the electric utility account holder.
- A parent or guardian who does not live in my home.
- The landlord/owner of my home.
- Someone who lives with me is the utility account holder.
- I don't know who pays my electric utility bill.

This is an important question for the study; if you don't know the answer, please take a moment to check a recent bill or ask someone who lives with you.

Since you are not the account holder (the person who pays the bill), we must receive permission from that person to access your energy data. If you have it, please fill out their contact information below. (You can still be part of this study by finishing the survey!)

Only answer this question if the following conditions are met:
Answer was 'Someone who lives with me is the utility account holder.' or 'A parent or guardian who does not live in my home.' or 'The landlord/owner of my home.' at question '7 [EnergyBill]' (Who is listed as the account holder on your electric utility bill?)

Please write your answer(s) here:
First Name:
Middle Initial:
Last Name:
Email address of account holder:
Phone number of account holder:

You can find the name of the account holder on a recent electricity bill from Burlington Electric Department. Please copy their name **exactly as it is displayed on the energy bill - including middle initial.**

About Your Home

This section contains questions about your local home. Think of this as where you currently live while interacting with UVM.

[]What best describes your home's property type? *

Please choose **only one** of the following:
- Single-family home
- Duplex
- Apartment/condo, 4 units or less in building/community
- Apartment/condo, 5 or more units in building/community
- Boarding house/individual room rental
- Recognized Fraternity/Sorority Chapter House
- Other

[]Estimate the size of your home, in square feet.

[]How many people live in your home, including you? *

Please write your answer(s) here:
Adult males (18+):
Adult females (18+):
Children:

[]Of the following appliances and devices, indicate how many are in your home. *

Please write your answer(s) here:
Dishwasher:

Refrigerator:
Mini-fridge:
Flat-screen Television (LED, LCD, etc):
Television (Not a flat-screen):
Clothes Dryer:
Clothes Washer:
Video game consoles (Wii, Xbox, PS4, etc.):
Programmable Thermostat:
Central air conditioner:
Small in-window air conditioner:

If you use an appliance in your building (e.g. washer/dryer in a common basement) that is not associated with your utility bill, do not count it here.
A "programmable thermostat" refers to a thermostat that can be set and is most likely digital.

[]Are the following utilities and services included in your rent? *

Only answer this question if the following conditions are met:
Answer was 'Yes' at question '2 [OffCampus]' (Do you live off-campus?) *and* Answer was 'Rent' at question '4 [RentOrOwn]' (Do you rent or own your home (your local residence)?)

Please choose the appropriate response for each item:

	Yes	Uncertain	No
Electricity	○	○	○
Heating Fuel (other than electricity, e.g. Gas)	○	○	○
Water	○	○	○
Internet	○	○	○
Television	○	○	○
Phone	○	○	○

[]What is the primary source of heating fuel for your home? *

Only answer this question if the following conditions are met:
Answer was 'Yes' at question '2 [OffCampus]' (Do you live off-campus?)
Please choose **only one** of the following:

- Natural Gas
- Propane
- Oil
- Electricity
- Firewood/Stove
- No heating fuel
- I don't know
- Other

[]Have you ever been exposed to information or education about home energy efficiency (in class, through the media, from your electric company, etc.)?*

Please choose **only one** of the following:

- Yes
- No

Influences

This section is to help understand where you get your information about energy and what influences your use of energy.

Please answer to the best of your ability.

[]How knowledgeable are you on the topic of energy efficiency?

Please choose **only one** of the following:

- Very knowledgable
- Somewhat knowledgeable
- About average
- Not very knowledgable
- Not knowledgable at all

[]Please rank how helpful you found the following potential sources of information about energy efficiency.*

All your answers must be different.

Please number each box in order of preference from 1 to 6

- Internet
- Friends or family
- Professors or classes
- Local utility company – Burlington Electric or Green Mountain Power
- Efficiency Vermont (a local organization)
- Newspapers or Magazines

[]How often do you discuss energy efficiency with friends, family or neighbors? *

Please choose **only one** of the following:

- Never
- Rarely
- Sometimes
- Often
- Very Often

[]Rank the following people according to how much they influence your decisions about energy use.*

All your answers must be different.

Please number each box in order of preference from 1 to 5

- Friends
- Neighbors
- A professor or teacher
- Work colleagues
- Family

[] How important are your home's energy efficiency and energy costs to you? *

Please choose **only one** of the following:

- Very important
- Somewhat important
- Not very important
- Not at all important

[]Right now, do you believe you have the ability to change your home's energy use?

Please choose **only one** of the following:

- Yes, definitely
- Yes, a little
- No
- I don't know

[]How concerned are you about climate change and greenhouse gas emissions? *

Please choose **only one** of the following:

- Very concerned
- Somewhat concerned
- Not very concerned
- Not at all concerned

[]Rank, in your opinion, what most influences the amount (and thus, costs) of energy used in your home.

All your answers must be different.

Please number each box in order of preference from 1 to 7

- Home size and construction
- My own behaviors and actions
- The behaviors and actions of others in the home
- Weather
- Government policies or rules of the property
- The electric company's rates
- Landlord or property manager

Energy Use and Your Home

These questions will help us understand how you are using energy in your home.

[]In your opinion, how energy efficient is your home? *

Please choose **only one** of the following:

- Not efficient at all
- Somewhat inefficient
- About average
- Somewhat efficient
- Very efficient
- I don't know

[]Have you spoken to your landlord or property manager about the efficiency of your rental unit? *

Please choose **only one** of the following:

- Yes
- No

[]Typically, with what frequency (in parentheses) do YOU perform the following actions? *

Please write your answer(s) here:

Dry clothes in the clothes dryer (loads per week)	
Run the dishwasher (times per week)	
Dry hair with hair dryer (times per day)	
Watch T.V. or other media source (hours per day)	

If you live with others, do not count their actions in your response.

[]Currently, how often do you ... *

Please choose the appropriate response for each item:

	Never	Rarely	Sometimes	Often	Always	N/A
Pull the window curtains at night to retain heat?	○	○	○	○	○	○
Switch off lights in empty rooms?	○	○	○	○	○	○
Add layers or a blanket to stay warm at home?	○	○	○	○	○	○
Shorten showers to conserve hot water?	○	○	○	○	○	○
Change thermostat settings to conserve energy?	○	○	○	○	○	○
Unplug devices not in use?	○	○	○	○	○	○

[]Rate how likely you are in the future to ... *

Please choose the appropriate response for each item:

	Not at all likely	Slightly likely	Moderately likely	Very likely	I don't know
Seek out information on how to conserve energy at home	○	○	○	○	○
Talk to a Landlord or Property Manager about efficiency upgrades	○	○	○	○	○
Change home thermostat settings to conserve energy	○	○	○	○	○
Insulate windows with plastic	○	○	○	○	○
Unplug devices not in use	○	○	○	○	○
Turn off lights when leaving a room	○	○	○	○	○
Reduce shower time to conserve hot water	○	○	○	○	○
Use additional clothing or blankets when cold	○	○	○	○	○

[] Consider that a 100-Watt incandescent light bulb uses 100 units of energy in one hour. How many units of energy do you think each of the following devices typically uses in one hour?*

Please write your answer(s) here:
___ A compact fluorescent light bulb as bright as a 100-Watt incandescent light bulb
___ An LED light bulb as bright as a 100-Watt incandescent light bulb
___ A laptop computer
___ A smartphone or tablet charger
___ An electric clothes dryer
___ A portable space heater
___ A room air-conditioner (e.g. window-mounted)
___ A central air-conditioner
___ A dishwasher
___ A standard refrigerator
___ A hair dryer

Enter a number less than 100 if you think the device uses less energy than a 100-Watt bulb. Enter a number greater than 100 if you think the device uses more energy than a 100-Watt bulb. Your best estimates are fine. Please enter whole numbers with no other text (not decimals, ranges, or percent signs).

About You

This set of questions gathers necessary contact information and verifies you are eligible to participate in the Home Energy Study. We'll contact you about the prize drawing and further participation in the study.

Once verified, and you participation is confirmed by the study organizers, this information will be removed from the survey records.

[]What's your name? *

Please write your answer(s) here:

First Name:	
Middle Initial:	
Last Name:	

[]Email address: *

[]UVM Netid: *

[]Are you a US citizen? *

Please choose **only one** of the following:

- Yes
- No

[]Which college are you associated with at UVM? *

Please choose **only one** of the following:

- Agriculture and Life Sciences
- Arts and Sciences
- Business
- Education and Social Services
- Engineering and Mathematical Sciences
- Environment and Natural Resources
- Nursing and Health Sciences
- College of Medicine
- Other

[]What is your major or field of study?

[]If you are selected in the prize drawing, you will win $100 and you may select a friend at UVM to also receive $100. Who would you like to receive $100?

[]If you are selected for the study, you may have a chance to borrow a small device about the size of an iPad that provides information about your home's electricity use. Are you willing to pick up the device at a location on campus (e.g. the Davis Center) and use it for the rest of this academic year (until about April 2016)?*

Please choose **only one** of the following:

- Yes
- No

[]When did you move in to your current home? *

[]When does your current lease end?

[]When do you expect to graduate?

[]How long do you expect to remain in your current residence? *

Please choose **only one** of the following:

- Until the end of my lease
- At least until the end of 2015
- At least until May 2016
- Other

[]Are you a Continuing Education student?

Please choose **only one** of the following:

- Yes
- No

Your Address

[]City *

[]Street Number *

[]Street Name

[]Apartment/Unit

[]Zip Code

Electricity Data Access

By completing this survey, you agree to allow your electricity utility to share your household's energy usage with the researchers to assess the impact of incentives and technology on consumption.

Your household can only be included in this study after we obtain permission from the rate payer.

Remember, the researchers will keep your information private, any personal information will be removed at the end of the study, and your energy use will never be traced back to you directly.

Thank you!

Thank you for completing the sign-up form.

Should be selected for the study, or if you win the prize drawing, we'll contact you soon. In the meantime, encourage your friends to sign up too and list you as their designated friend in the prize drawing!

The link for the form is **http://go.uvm.edu/energystudy**

A.2 Post-treatment Survey

Off-campus Energy Study Spring 2016 Post-Study Survey

Please complete this survey to conclude your household's participation in the UVM Off-campus Home Energy Study.

All responses are kept confidential and personal information will be removed at the end of the study.

To go backward or forward in the form, use the "Previous" and "Next" buttons at the bottom of the screen. **Do not use your web browser's back or forward buttons.**

Please read these details carefully.

This is a study about household energy use. No personally-identifiable information from your responses will be shared. Any personal information collected in this form is to be sure you receive any compensation you've earned.

This is a survey for households that have participated in the study. If you completed the screening survey during Fall 2015, some of these questions may seem familiar while others are new.

Please answer all questions to the best of your ability and do not look up "correct" answers unless advised to do so.

When you complete this form, **you will be entered in a prize drawing**. If your name is drawn, you will receive **$25** (plus any additional compensation your household already earned in the study).

This research is conducted by doctoral students in the UVM Rubenstein School of Environment & Natural Resources affiliated with the Gund Institute for Ecological Economics and the UVM Smart Grid IGERT. The study is supported by the UVM Clean Energy Fund.

To begin the form, click "Next" below.

There are 40 questions in this survey

Household Identification

This section will help connect your responses on this form to any responses from the pre-study form.

[]Enter your unique household code:

Please write your answer here:

You may have received a special code for your home in an email, either from the study coordinators or someone who lives with you. If you did, enter it here.

[] Who is listed as the account holder on your electric utility bill?*

Please choose **only one** of the following:

- I am listed as the electric utility account holder.
- A parent or guardian who does not live in my home.
- The landlord/owner of my home.
- Someone who lives with me is the utility account holder.
- I don't know who pays my electric utility bill.

[]Some of the households in the Energy Study received an in-home display. Were you in one of these households?*

Please choose **only one** of the following:

- Yes
- No
- I don't know

[]Some of the households in the Energy Study received incentives to alter their energy use. Were you in one of these households? *

Please choose **only one** of the following:

- Yes
- No
- I don't know

Your IHD Experience

This section is about your experience using the in-home display.

[]Were you able to successfully set up your IHD? *

Please choose **only one** of the following:

- Yes
- No

"Successfully" means that the device was connected to your meter, displayed energy information, and you were able to connect it to your home's wifi network.

[]Please indicate whether you agree or disagree with the following statements:*

Answer options:
Strongly disagree -> Somewhat disagree ->
Neutral -> Somewhat agree -> Strongly agree | N/A

Please choose the appropriate response for each item:

- The IHD was easy to set up.
- The IHD is easy to use.
- The IHD has an appealing display I want to view.
- The IHD displays useful information regarding my home's energy consumption.
- The IHD helped me learn more about my own energy consumption.
- I made changes in my own behavior because of the IHD.
- The IHD makes it easier to impact my home's energy consumption.
- The people I live with made changes in their behavior because of the IHD.
- The IHD specifically made me want to discuss energy efficiency with my landlord or property manager.
- The $ amount displayed on the IHD motivates me to conserve energy.

[]Tell us a story (or some stories) about your experience using the IHD. Anything at all!

Please write your answer here:

Consider the device setup, the placement of the device, whether you put it away after a while or not, any conversations or insights, changes you may have made, whether you used the app or website vs the device, etc.

Your Incentive Experience

This section is about your experience with incentives to change your home's electricity consumption.

[]Did you read the original incentive instructions email? *

Please choose **only one** of the following:

- Yes
- No

[]Please indicate whether you agree or disagree with the following statements:*

Answer options:
Strongly disagree -> Somewhat disagree -> Neutral -> Somewhat agree -> Strongly agree | N/A

- Please choose the appropriate response for each item:
- The energy reduction incentive instructions were clear.
- The energy shifting incentive instructions were clear.
- The energy reduction incentive amount* was enough to make me change my behavior.
- The energy shifting incentive amount^ was enough to make me change my behavior.
- The people I live with changed their behavior because of the energy reduction* incentive.
- The people I live with changed their behavior because of the energy shifting^ incentive.
- It was easy to make changes that reduced energy use.
- It was easy to shift what times I used energy.
- The incentives made me think more about my home's energy use.
- The incentives, specifically, made me want to discuss energy efficiency with my landlord or property manager.
- I thought I had a good chance to win at least one of these incentive rewards.

** You'd receive the total value on your bill if you were the top-conserving household.*
^ If you were the top energy-shifting household that day, you'd receive $20.

[]Tell us a story (or some stories) about your experience with the incentives. Anything at all!

Please write your answer here:

About Your Home

This section contains questions about your local home. Think of this as where you currently live while interacting with UVM.

[]Estimate the size of your home, in square feet.

[]How many people live in your home, including you? *

Please write your answer(s) here:
Adult males (18+):
Adult females (18+):
Children:

[]On a typical week day, about how many hours per day is no one home? *

Give your best estimate in hours. If someone is always home, enter a zero (0).

[]What is the primary source of heating fuel for your home? *

Please choose **only one** of the following:

- Natural Gas
- Propane
- Oil
- Electricity
- Firewood/Stove
- No heating fuel
- I don't know
- Other

[]Have you ever been exposed to information or education about home energy efficiency (in class, through the media, from your electric company, etc.)? *

Please choose **only one** of the following:

- Yes
- No

Influences

This section is to help understand where you get your information about energy and what influences your use of energy.
Please answer to the best of your ability.

[] How knowledgeable are you on the topic of energy efficiency?

Please choose **only one** of the following:

- Very knowledgable
- Somewhat knowledgeable
- About average
- Not very knowledgable
- Not knowledgable at all

[]Please rank how helpful you found the following potential sources of information about energy efficiency.*

All your answers must be different.

Please number each box in order of preference from 1 to 6

- Internet
- Friends or family
- Professors or classes
- Local utility company – Burlington Electric or Green Mountain Power
- Efficiency Vermont (a local organization)
- Newspapers or Magazines

[]How often do you discuss energy efficiency with friends, family or neighbors? *

Please choose **only one** of the following:

- Never
- Rarely
- Sometimes
- Often
- Very Often

[]Rank the following people according to how much they influence your decisions about energy use.*

All your answers must be different.

Please number each box in order of preference from 1 to 5

- Friends
- Neighbors
- A professor or teacher
- Work colleagues
- Family

[] How important are your home's energy efficiency and energy costs to you?*

Please choose **only one** of the following:
- Very important
- Somewhat important
- Not very important
- Not at all important

[]Right now, do you believe you have the ability to change your home's energy use?

Please choose **only one** of the following:
- Yes, definitely
- Yes, a little
- No
- I don't know

[]How concerned are you about climate change and greenhouse gas emissions? *

Please choose **only one** of the following:
- Very concerned
- Somewhat concerned
- Not very concerned
- Not at all concerned

[]Rank, in your opinion, what most influences the amount (and thus, costs) of energy used in your home.

All your answers must be different.

Please number each box in order of preference from 1 to 7

- Home size and construction
- My own behaviors and actions
- The behaviors and actions of others in the home
- Weather
- Government policies or rules of the property
- The electric company's rates
- Landlord or property manager

Energy Use and Your Home

These questions will help us understand how you are using energy in your home.

[]In your opinion, how energy efficient is your home? *

Please choose **only one** of the following:

- Not efficient at all
- Somewhat inefficient
- About average
- Somewhat efficient
- Very efficient
- I don't know

[]Have you spoken to your landlord or property manager about the efficiency of your home? *

Please choose **only one** of the following:

- Yes
- No

[]Typically, with what frequency (in parentheses) do YOU perform the following actions? *

Please write your answer(s) here:
Dry clothes in the clothes dryer (loads per week)
Run the dishwasher (times per week)
Dry hair with hair dryer (times per day)
Watch T.V. or other media source (hours per day)

If you live with others, do not count their actions in your response.

[]Currently, how often do you ... *

Please choose the appropriate response for each item:

Never - Rarely - Sometimes - Often - Always - N/A

Pull the window curtains at night to retain heat?
Switch off lights in empty rooms?
Add layers or a blanket to stay warm at home?
Shorten showers to conserve hot water?
Change thermostat settings to conserve energy?
Unplug devices not in use?

[]Rate how likely you are in the future to ... *

Not at all likely - Slightly likely - I don't know - Moderately likely - Very likely

Please choose the appropriate response for each item:

Seek out information on how to conserve energy at home
Talk to a Landlord or Property Manager about efficiency upgrades
Change home thermostat settings to conserve energy
Insulate windows with plastic
Unplug devices not in use
Turn off lights when leaving a room
Reduce shower time to conserve hot water
Use additional clothing or blankets when cold

[] Consider that a 100-Watt incandescent light bulb uses 100 units of energy in one hour. How many units of energy do you think each of the following devices typically uses in one hour?*

Please write your answer(s) here:
___ A compact fluorescent light bulb as bright as a 100-Watt incandescent light bulb
___ An LED light bulb as bright as a 100-Watt incandescent light bulb
___ A laptop computer
___ A smartphone or tablet charger
___ An electric clothes dryer
___ A portable space heater
___ A room air-conditioner (e.g. window-mounted)
___ A central air-conditioner
___ A dishwasher
___ A standard refrigerator
___ A hair dryer

Enter a number less than 100 if you think the device uses less energy than a 100-Watt bulb. Enter a number greater than 100 if you think the device uses more energy than a 100-Watt bulb. Your best estimates are fine. Please enter whole numbers with no other text (not decimals, ranges, or percent signs).

[]I pay close attention to my energy bill: *

Please choose **only one** of the following:

- Yes
- No

[]Suppose a utility was going to offer you an incentive to change how and when you use energy in 24 hours. What is the best way to reach you so you'd know about the incentive?

All your answers must be different.

Please number each box in order of preference from 1 to 5

- Automated Phone Call
- Text Message
- Email
- Mailer/Postcard
- Mobile App Notification

About You

This set of questions gathers necessary contact information and verifies you are eligible to participate in the Home Energy Study. We'll contact you about the prize drawing and further participation in the study.
Once verified, and you participation is confirmed by the study organizers, this information will be removed from the survey records.

[]What is your *primary* relationship to the University of Vermont? *

Please choose **only one** of the following:

- Undergraduate Student
- Graduate Student
- Medical Student
- Faculty/Staff
- Alumni
- Living with a current UVM student
- No relationship to UVM
- Other:

Choose the answer you identify with the most. For example, if you are a full-time staff and also take graduate courses, choose Faculty/Staff.

[]What's your name? *

Please write your answer(s) here:

First Name:	
Middle Initial:	
Last Name:	

[]If you are compensated in the study, please provide the best way to reach you:

Please write your answer(s) here:

Phone:	
Email:	
Text message:	

Enter this information if you prefer to be contacted this way. We'll default to email.

[]UVM Netid: *

Only answer this question if the following conditions are met:
Answer was 'Graduate Student' or 'Undergraduate Student' or 'Faculty/Staff' or 'Medical Student' at question '32 [UVMStatus]' (What is your primary relationship to the University of Vermont?)
Please write your answer here:

This will verify your affiliation with UVM. e.g., "mkapoodle"

[]Are you a US citizen? *

Please choose **only one** of the following:
- Yes
- No

[]Which college are you associated with at UVM? *

Only answer this question if the following conditions are met:
Answer was 'Undergraduate Student' *or* 'Faculty/Staff' *or* 'Graduate Student' *or* 'Medical Student' at question '32 [UVMStatus]' (What is your primary relationship to the University of Vermont?)

Please choose **only one** of the following:
- Agriculture and Life Sciences
- Arts and Sciences
- Business
- Education and Social Services
- Engineering and Mathematical Sciences
- Environment and Natural Resources
- Nursing and Health Sciences
- College of Medicine
- Other

[]What is your current major, field of study, or profession?

Please write your answer here:

If you're a current student, enter a major/field of study. If you're not a student, enter your profession.

[]When do you plan to move out of your current home?

Please enter a date:
Type in the date in the format MM-DD-YYYY or use the date picker.

[]When do you expect to graduate?

Only answer this question if the following conditions are met:
Please enter a date:
Type in the date in the format MM-DD-YYYY or use the date picker.

Thank you for finishing the survey and participating in the Off-campus Energy Study!

If you win the prize drawing, we'll contact you soon.

B Incentive Instructions

Subjects selected to receive the incentive treatment were sent the following message, which was also available on the study website:

Incentive Instructions & Details

Do these to win the competition:

1. **Reduce your energy consumption.** For the duration of the study, reduce your household's overall electricity consumption.
2. **Shift the timing of your energy consumption.** During the study, we will alert you in advance of special **"peak events"** on random weekdays. The alerts will give you details, but you'll typically be asked to avoid using electricity as much as possible during certain **"peak hours"** of the day. For this incentive, we are asking you to shift *when* you use electricity, not necessarily *how much* you use in a day. Expect 1-4 peak events per month during the study. Check your email for messages from oec@uvm.edu - peak event notifications will come from this address.

How you win money for *energy reduction*:

- Your daily energy use during the study period will be compared to a baseline derived from your energy use prior to the start of the study. For each month in the study (February to May), the total change from your daily baseline will be calculated.
- Your total monthly energy reduction will be ranked in comparison to other households in the study. A percentage of your electricity bill that month will be reimbursed to you based on your ranking. The top-ranking households each month will get reimbursed for their entire electric bill!

How you win money for *energy shifting*:

- For each peak event, electricity used during peak hours (the "peak event") will be compared to what your home typically consumes during these hours (your "peak baseline"). For each month in the study, the total change from your peak baseline during peak events will be calculated.
- Your ability to shift energy use away from these peak hours will be ranked in comparison to other households in the study. There will be a reward made available for peak events each month, and your rank determines your portion of that money.

When possible, you will receive periodic updates on your status in the competition. At the end of the study, we'll schedule a time for you to get your earnings. Additionally, you will receive a special report about your energy use at the conclusion of the study.