BEHAVIORAL INTERVENTIONS IN ENERGY CONSUMPTION

by

Joel Hicks
A Dissertation
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of
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Public Policy

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DEDICATION

This dissertation is dedicated to my loving partner, friend, coach, trainer, cheerleader, sage, and part-time therapist, Dr. Megan Nesbitt.

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This work is a reflection of what every good public policy Ph.D. program should be; a place that allows the student to explore many spaces and interests until he/she finds something about which they are passionate. I commend the entire faculty at George Mason University's Schar School of Policy and Government for encouraging me to engage with my interests in a very tactile way, through a field experiment. I had strong support from every corner, even during moments where the project looked like it might not get off the ground.

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Advanced Metering Infrastructure	AMI
British Thermal Unit	BTU
Carbon Intensity	CI
Common Pool Resource	CPR
Corporate Average Fuel Economy	CAFE
Critical Peak Pricing	CPP
Demand Response	DR
Demand Side Management	DSM
Department of Energy	DOE
Distributed Energy Resources	DER
Energy Efficiency Escrow	EEE
Energy Efficiency Resource Standard	EERS
Energy Independence and Security Act	EISA
Energy Information Administration	EIA
Energy Intensity	EI
Energy Service Company	ESCO
Environmentally Responsible Behavior	ERB
Federal Energy Regulatory Commission	FERC
Federal Trade Commission	FTC
Greenhouse gas	GHG
Gross Domestic Product	GDP
Heating, Ventilation, and Air Conditioning	HVAC
Home Energy Report	HER
Human Resources	HR
Independent System Operator	ISO
Information Technology	IT
In-Home Display	IHD
Institutional Review Board	IRB
Integrated Resource Planning	IRP
Intelligent Smart Metering	ISM
Intended Nationally Determined Contributions	INDC
Investor-Owned Utility	IOU
Kilowatt-Hour	kWh
Light Emitting Diode	LED
Load Serving Entity	LSE
Local Energy Distribution Company	LDC

Marginal Abatement Cost Curve .... MACC
Midcontinent Independent System Operator .... MISO
Net Present Value .... NPV
Ordinary Least Squares .... OLS
Pay for Performance P4P
Peak Time Rebate .... PTR
Policy-Induced Improvements .... PII
Physical, Technical, and Economic Model .... PTEM
Programmable Communicating Thermostat .... PCT
Public Utility Commission .... PUC
Public Utility Regulatory Policies Act .... PURPA
Randomized Control Trial .... RCT
Realtime Pricing .... RTP
Regional Transmission Organization .... RTO
Renewable Portfolio Standard .... RPS
Research and Development .... R&D
Theory of Planned Behavior .... TPB
Time-of-use .... TOU
United Nations Framework Convention on Climate Change .... UNFCCC
Values, Beliefs, and Norms .... VBN
Zero Cost Breakthrough .... ZCB

ABSTRACT

BEHAVIORAL INTERVENTIONS IN ENERGY CONSUMPTION

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The “Energy Paradox”, whereby consumers undervalue energy efficiency investments, is one of the most puzzling phenomenon for energy policy researchers. Within this sector behavioral economics is beginning to provide understandings that cannot be explained using neoclassical economic theory. Using the results of a field experiment designed for this dissertation, several theories of behavior toward electricity consumption are examined. One of those theories, prospect theory, is applied for the first time using an incentive structure, or frame, called an Energy Efficiency Escrow (EEE). This treatment is compared with a traditional financial incentive structure called pay-for-performance (P4P), which itself has not yet been applied to the residential household energy sector. Although there were substantial energy reductions in both groups, the research found that consumers who were forced to calculate their potential gains (P4P-implicit gains) conserved more energy than those who were constantly updated on their potential losses (EEE-explicit losses). The P4P group also underestimated their final reward relative to

the EEE group. Users who found elements of the EEE confusing actually increased their energy usage relative to their baseline. Additionally, higher baseline energy users in both groups conserved a higher percentage of their baseline energy use relative to lower baseline energy users.

INTRODUCTION

This dissertation provides new insights in how consumers respond to financial incentives targeted at energy consumption reduction. It provides results from a randomized control trial (RCT) conducted over nine months with energy users residing on a college campus. The first major section,

Energy demand policy and the “energy paradox”, provides a policy and regulatory backdrop that motivates the research. It suggests that energy efficiency suffers from regulatory and structural barriers that prevent it from being an even more effective GHG reduction tool while simultaneously reducing energy costs. Currently deployed technology, including AMIs, are being under-utilized in view of the ability to leverage real-time usage feedback for behavioral changes.

The next major section,

Theories of Behavior applied to Energy Consumption, provides an overview of the major behavioral theories that have been applied (or have the potential to be applied) to energy consumption. Where appropriate, empirical evidence is provided with their associated impacts. The reader will notice that many theories that appear relevant to energy consumption have little, if any, reliable studies to estimate their impact. In fact, behavioral studies applied to energy consumption are nascent with a large potential to be studied further. Prospect theory remains one of the most understudied areas of behavioral economics applied to energy consumption.

The next two sections,

Research Design and

Field Experiment Results, provide the details of the field experiment that address the four primary research questions. Several unexpected insights were also discovered from the field experiment. Those that the author assessed as particularly relevant for further study are provided in more detail. Finally, the

Conclusions and Policy Implications section is the author's attempt to identify the most promising ways to extend the research in ways that could make it scalable and/or integrable with other behavioral traits.

ENERGY DEMAND POLICY AND THE "ENERGY PARADOX"

The Relevance of Energy Efficiency Policies

Energy efficiency and conservation is largely responsible for the decoupling of economic growth with electricity demand, which has flattened over the last thirty years. Nevertheless, utility companies and regulators have struggled to properly incentivize energy efficiency and conservation within a rate regulation scheme that is based on recovery of capital assets, almost exclusively on the supply side. In fact, only a small segment of utility rate recovery goes toward energy efficiency and conservation. Although some states employ energy efficiency resource standards, they are typically modest and do not sufficiently employ new technologies that could help realize greater reductions. This is especially relevant since the cost of mitigating (or conserving) a kilowatt-hour of energy is lower than adding the equivalent amount of generating capacity (see Figure 1); and a smaller footprint of capital assets would yield greater savings to *all* energy consumers. In other words, individual energy efficiency improvements can have widespread social benefits. The integration of smart meters and devices with cloud computing is beginning to gain the attention of energy regulators, who are looking more closely at how new energy services can be employed.

Questions remain as to the efficacy of incentives designed to reduce consumption. For instance, are consumers being under-rewarded for reducing their baseline usage relative to lower energy bills and occasional rebates? For instance, a substantial fraction of user energy costs are not for actual usage but for maintenance of supply infrastructure, sometimes referred to as demand charges, while rebates suffer from free-ridership problems, where informed users are generally inclined to invest in energy efficiency without the rebate incentive. Behavioral economics has a role to play in answering some of these questions, many with proven applications in other public policy fields. This research takes a fresh look at several theories of behavior to see if there are measurable reductions that can be employed to incentivize energy conservation. The costs and benefits of these "nudges" will be used to help inform regulators as to how new demand-side technologies might enable more cost-effective alternatives to supply side measures. Even a modest reduction in energy demand would have tremendous impact on an electricity industry with over $380 billion in revenues.

The Energy Efficiency Gap

The policy issue that is most immediately addressed in this research is the "energy efficiency gap" or "energy paradox", defined as the significant difference between observed levels of energy efficiency and the notional optimal level of energy use[1] (Jaffe, Newell, & Stavins, 2004). The potential to reduce energy consumption through positive net-present value (NPV)[2] energy efficiency investments has been well documented

[1] This is also referred to as the "energy paradox", described by Jaffe and Stavins as a slower than socially optimal rate of diffusion of energy efficiency products (Jaffe & Stavins, 1994b). Of course, "optimal level" is itself subject to multiple interpretations; for instance, the engineering-optimal levels may be different than what individual firms and consumers are willing to pursue if they are unwilling to commit time to monitor price signals or conduct research in exchange for less energy efficient outcomes (Allcott, Mullainathan, & Taubinsky, 2014).
[2] Alternately described as when the present discounted value of future energy savings exceeds the upfront cost.

(eschwass, 2016; Frankel, Heck, & Tai, 2013). One of the most heavily cited engineering analyses suggests that the U.S. economy could reduce demand by 23 percent at a net present value of $700 billion (Granade et al., 2009).

Neo-classical economics suggests that if investments in energy efficiency make consumers better off, then these gains, or investments, should have been realized. In fact, over thirty years of empirical research has demonstrated consistent consumer failure to make positive net present value energy efficiency investments (Gillingham & Palmer, 2013). These investment inefficiencies suggest that government intervention may be warranted by providing: 1) information to imperfectly informed consumers, and 2) policies that subsidize or mandate energy efficiency (Allcott & Greenstone, 2012). Because energy efficiency, on a per-kWh basis, is often more economical than adding new generation (eschwass, 2016), there exists a strong policy argument for incentivizing efficiency as an alternative to supply side measures. Because most state rate regulation is structured to reward utilities based on increased demand (and therefore supply) via cost recovery on capital expenses, there are few programs that are designed to incentivize customers to reduce consumption. In fact, it provides the fundamental argument for promoting energy efficiency as an energy resource capable of displacing electricity generation (ACEEE, 2010).

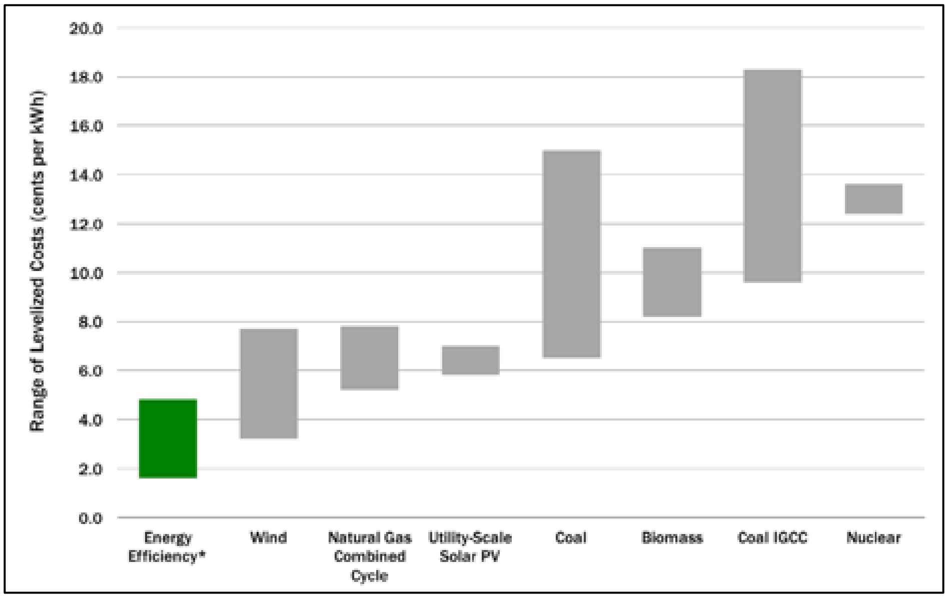


Figure 1: Levelized Cost of Energy Efficiency compared to New Generation Sources

Models of Demand

Understanding energy demand continues to be a challenge for policy makers as there are multiple models, each of which provide a useful perspective, but none that are sufficient for meeting societal short and long-term objectives. Four of the primary ones include, 1) the physical, technical, and economic model (PTEM), 2) an energy services approach, 3) social practice theories, and 4) socio-technical transitions (Ekins, Bradshaw, & Watson, 2015, p. 134).

Physical, Technical, and Economic model (PTEM)

The PTEM model (as its name suggests) emphasizes technological and economic explanations of energy consumption. It is based primarily on engineering and economic "best case" scenarios and typically does not factor in economical, behavioral, social, or psychological constraints that may prevent the diffusion of energy efficiency technologies. These models are common in discussing the "energy efficiency gap", as they quantitatively show the difference between as-is and ideal improvements. As an example, one commonly referenced study on cost efficiency in reducing GHGs, reviewing both energy efficiency and carbon intensity improvements based on marginal abatement cost curves (MACCs) (Figure 2), represents a purely PTEM approach to energy demand (and supply). Energy demand is essentially reduced to variables such as incomes, physical circumstances, and technological availability.

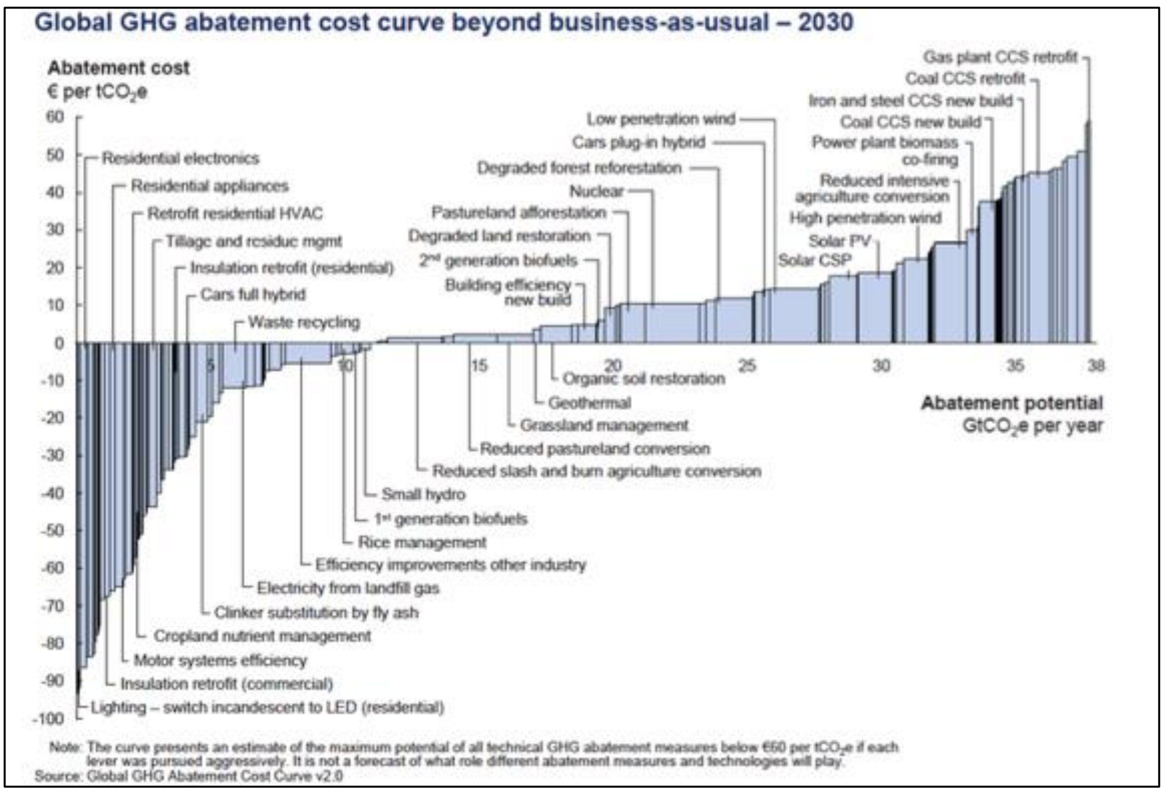


Figure 2: Global GHG Abatement Cost Curve ("Greenhouse gas abatement cost curves | Sustainability & Resource Productivity | McKinsey & Company,")

There is a substantial debate about the accuracies of many PTEM models, placing some doubt on some of the estimates. For instance, a recent weatherization study of 30,000 households in Michigan found the upfront investment costs are about twice the actual energy savings -or- an average rate of return of approximately negative 7.8% annually (Fowlie, Greenstone, & Wolfram, 2018). Other studies have yielded similar findings (Allcott & Greenstone, 2017).

Energy Services and Social Practices Models

An energy services approach to energy demand attempts to separate the activities of daily life (e.g. mobility, sheltering from weather, cooking, communicating) from energy demanded at the point of use. In other words, it fundamentally separates future consumption habits with past consumption paradigms. The social practice approach to energy demand fundamentally challenges the assumption that consumption habits are individually or technologically determined but, rather, asserts that they are socially constructed. Practices are sustained by values and norms, institutionalized rules, know-how and routines, and materials, products, and technologies (Reckwitz, 2002; Schatzki, 1996). In addition to personal behavioral inconsistencies, social practices can partially explain why economic incentives and improved information do not always translate to effective policies.

Socio-technical Model

The socio-technical model views energy systems (e.g. electricity delivery, transportation networks, fossil fuel delivery systems) as inherently large, interconnected, and complex. Put simply, “understanding energy demand is a socio-technical problem rather than one that is either social or technical” (Ekins et al., 2015).

A large socio-technical transition is “a major technological transformation in the way societal functions….are fulfilled, not only technological changes, but also changes in user practices, regulation, industrial networks, infrastructure and social meaning”[3] (Geels, 2002). Supporting systems of the sector are highly intermeshed and within this model, the demand for energy is not purely reflective of price signals or consumer attitudes, but something that is ‘systematically configured’ over the long-term under both social and technological influences (Vliet, Chappells, & Shove, 2005). Socio-technical transitions are concerned less with strictly economic (PTEM) drivers of technological changes than with the roles, influences, and relationship of actors and social institutions at several levels. They are also reflective of endogenous and exogenous influences, the latter of which can have tremendous influence on transitions. This model, therefore, is well suited for evaluating the role of governance.

Large socio-technical transitions represent a unique field of research and, for a variety of reasons, the U.S. energy sector is undergoing a major shift in how energy is delivered to consumers. Within the context of socio-technical transitions, the term “regime” is used to represent a series of complex, nested real-world phenomena consisting of natural and artificial physical elements as well as social, economic, cultural, and cognitive attributes. Within these regimes forces are often at complete odds with one

[3] Although social practices (described earlier) are part of the model, they are largely contextual in view of the fact that practices are often limited by options presented by ‘systems of provision’, or socio-technical complexes.

another while societies continue to struggle to make and implement the necessary changes to improve their collective well-being. Of course, effective governance within these large transitions, although not always sufficient to achieve positive outcomes, is certainly required. One author identified three properties that make the socio-technical energy system so challenging, 1) its complexity, 2) high costs, and 3) its strong path dependency (Goldthau & Sovacool, 2012).

This research, and other behavior modification studies, inform both the social practice and socio-technical views of energy systems. It embraces the idea that technology itself is a means by which attitudes and behaviors can be changed.

Energy Efficiency as a Market Failure

The energy efficiency gap is recognized as a public policy challenge at various level of local, state, and federal government. Certainly, any strong evidence suggesting the non-optimal allocation of goods and services will, and should, get the attention of policy makers. To understand the challenges of supply-side and demand-side electricity regulation it is fitting to examine neoclassic microeconomic theory, whereby government interventions are necessary to correct for market failures: information asymmetry, pure public goods, monopolies, and externalities. One or more of these can lead to suboptimal outcomes such as destructive competition, scarcity, and innovation stagnation, where socially optimal prices and quantities are not realized.

Perhaps at its most fundamental level, the efficiency gap originates from the very system by which energy services were first regulated. Energy has long been regarded as a public necessity within the U.S., and this fact heavily shaped how utility services were initially organized. Generous government subsidies and monopoly status granted to energy companies largely protected those companies from competition, compelling them with a "duty to serve" all customers, while allowing them to charge "just and reasonable" rates for their service. Low consumer costs and energy abundance have historically attracted more political support than have externalities, social welfare, and demand side management (Freeman, 1973).The resulting rate-making structure of public utilities has not fundamentally changed in the last eighty years and is still based on receiving a fair rate of return on capital investments. This is a barrier if the goal is to encourage utility companies to reduce consumption by encouraging energy efficiency.

Historically, commercial and industrial energy consumers have invested in energy efficiency improvements more so than residential household consumers. This is partially understandable in view of the exigencies of business competitiveness. However, the residential household sector accounted for 38.5 percent of all electricity consumed in the U.S. in 2018 according to the EIA.

Theories of Regulation

Public interest theory, as a *normative* theory of regulation, suggests that regulation is one way of addressing market failures by responding to the demand of the public for the correction of inefficient or inequitable market practices. However, one major criticism of this theory is that there is no guarantee that a governmental response will deliver outcomes that are better than other alternatives, including no action (Grossman, 2013). The predominant theory suggesting that regulation may result in *suboptimal* outcomes is capture theory, where interest groups, often competing with each other, use regulation to maximize the incomes of their members (Posner, 1974).

Energy Efficiency as a Market Failure Solution

Another class of market failures, and one particularly relevant for energy policy, are externalities. This occurs when, in the process of producing or consuming certain goods or services, harmful or beneficial side effects are borne by people not directly involved in the market activities (Browning & Zupan, 2012, p. 567). Options for policy makers include: 1) doing nothing, 2) allocating property rights such that agents can negotiate contracts to account for the externality[4], 3) imposing a tax (preferably a Pigouvian one), or 4) regulating the good or service that is producing the externality.

Most environmental problems can be classified into a complicated policy-making domain called, "commons problems", where self-interest and public interests have differing optimal solutions (Stone, 2012, p. 25). Global climate change can be regarded as a common pool resource (CPR) problem in that the earth's atmosphere can be universally exploited, or contaminated, without the ability to exclude the useful benefits deriving from it. Per public choice theory, policy proposals with concentrated costs and diffuse benefits will tend to be at a disadvantage politically, particularly in terms of resources (Olson, 1965; Stone, 2012).

One major argument for the "federalization" of energy policy is the importance of the environmental on social health and well-being. Some of the earliest government

[4] As Coase points out that transaction costs, which includes identifying affected parties, conducting negotiations, drawing up contracts, and conducting inspections, can be "sufficiently costly at any rate to prevent many transactions that would be carried out in a world in which the pricing system worked without cost." (Coase, 1960, p. 15)

interventions in electric generation addressed harmful health-related effects from emissions, primarily from coal plants. A 2009 study estimated that the annual *non-climate* related costs of 406 coal-fired plants was $62 billion, or 3.2 cents/kWh, approaching 50 percent of the average cost of electricity[5] (National Research Council, 2010). Another study examining the health effects of the entire life-cycle cost of the coal industry concluded that externalities cost the American public as much as $500 billion, which, if internalized, would double or triple the cost of coal-powered electricity generation (Epstein et al., 2011). Clearly, the *direct* health effects of harmful, even toxic, emissions from fossil-fueled plants helped to rally political support for tougher regulations and a successful market-based sulfur-dioxide (SO_2) program of reduction (Geri & McNabb, 2011).

The cost, and sometimes even the acknowledgement, of climate change remains a political obstacle in the U.S. This is particularly relevant for the electricity sector, which accounts for around 28 percent of all U.S. GHG emissions Figure 3. Since the worst effects of climate change are decades away, debate regarding the optimal abatement strategy influences any potential carbon-pricing policy. Two prominent climate change economists[6] reach different conclusions regarding cost of abatement efforts largely due to differing assumptions as to the appropriate discount rate.

[5] the report went on to say that a “relatively small number of plants -- 10 percent of the total number -- accounted for 43 percent of the damages. By 2030, non-climate damages are estimated to fall to 1.7 cents per kwh.

[6] Stern (N. H. Stern & Treasury, 2007) and Nordhaus (Nordhaus, 1991).

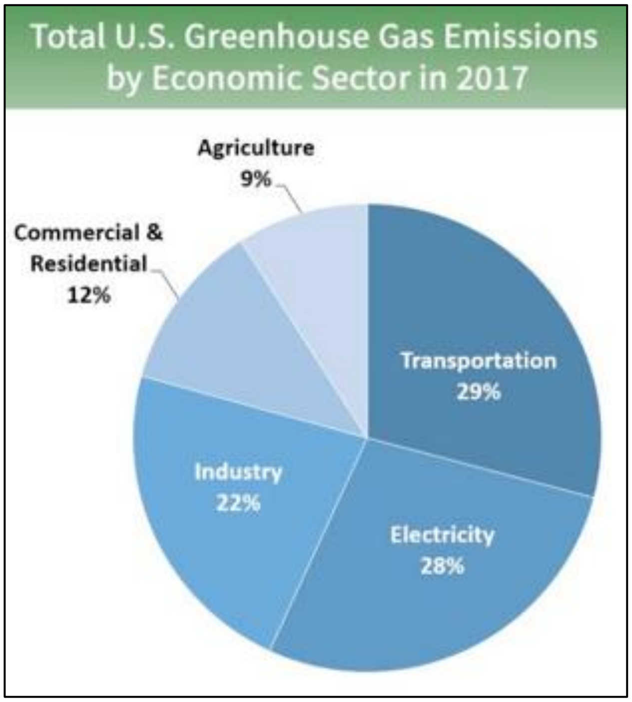


Figure 3: Portion of GHG's due to Electricity Consumption (EIA, 2017)

The 2015 COP-21 agreement in Paris between the world's leading carbon-emitting nations places increased impetus on U.S. states to assess their respective carbon mitigation policies. This reflects the fact that states have historically had more of a role in developing energy policies than the federal government, but also the recent political incoherence within the U.S. federal government to acknowledge the threat of climate change and/or formulate effective policies and commit financial resources toward mitigating GHG emissions. Still, many states have committed to the INDC's submitted by the U.S. to the UNFCCC in shaping energy policies.

Energy efficiency as a tool to address climate change is by no means a new concept. Many of the carbon "stabilization wedges", aggregated together to bend the global carbon emissions curve using *proven* technologies, look heavily toward energy efficiency improvements (Pacala & Socolow, 2004). Others have calculated that "nudges" or behavioral changes alone could account for an entire stabilization wedge, or 1.8-2.2 quadrillion BTU's a year for U.S. households (equivalent to 16-20 percent of residential demand) (Frankel et al., 2013). One of the recommended tools includes improved information and feedback to consumers. This research explores how feedback, coupled with financial incentives, can be used to change user behavior.

Historically, efforts by federal and state governments to reduce the "carbon intensity of the economy" (carbon intensity + energy intensity) have tended to focus on production-side policies, a mixture of incentives and regulations (e.g. renewable portfolio standards, renewable subsidies, generation facility emission limits). However, in most states, energy intensity (EI) reductions, reflective of demand side and consumer behavioral changes, continue to outpace carbon intensity (CI) reductions in directly contributing to carbon reductions. This fact suggests that policies and resources directed on the demand side of the energy system should be enhanced.

Given the current state of rate regulation it is likely that energy conservation is undervalued. This is evident by how residential customers are billed for energy use. A large portion of what a customer pays for, whether they actually use any energy or not, is the capacity, or demand, charge. In other words, a premium paid to the utility to maintain a sufficient generation capacity to provide reliable, uninterrupted power throughout the year, including during peak demand. So, an energy consumer is paying interest on capital investments made by the utility company in addition to the actual generation charges consistent with her monthly use. In fact, utility companies will often lower capacity charges for customers with *higher* average energy usage. Here is one extreme case from a customer in Texas, “A customer who used 1,200 kilowatt hours - about average monthly use for Texas residences, according to the U.S. Energy Information Administration - would have an electric bill around $78. But if the customer reduced energy consumption by a third to 800 kilowatt hours, the monthly bill would *rise* about $17 because the customer would lose out on the credit” (Holeywell, 2015). The clear problem with this type of regulatory structure is that it *encourages* more consumption, which subsequently increases the need for more generation and transmission capacity. Clearly, this is not socially optimal. A more thorough assessment of how prevalent this mixed incentive is clearly warranted.

The Kaya Equation

The Kaya Equation (Equation 1) is a useful way of showing how production and demand side policies influence carbon emissions (Raupach et al., 2007); in fact, the Energy Information Agency (EIA) uses it as the primary determinant of U.S. state carbon emissions by tracking state production and consumption levels and assessing carbon emissions based on several factors, including fuel types, energy loads, and characteristics of generating facilities (EIA, 2019). Because each type of fuel has a unique emission profile (e.g. carbon emissions per BTU per fuel type) a rather accurate carbon footprint can be calculated.

Equation 1: The Kaya Equation[7]

$$CO_2 Emissions = \left[\frac{CO_2\ emitted}{Unit\ of\ energy} \times \frac{Units\ of\ Energy}{Unit\ of\ GDP}\right] \times \frac{GDP}{Capita} \times Population$$

The first two terms of Equation 1 account for all factors that can be managed within the realm of energy policy and represent, respectively, the supply and demand variables of the energy economy. For instance, improvements to electricity generation facilities' carbon emissions affect CI, or the amount of carbon emitted for a given unit of energy produced. By comparison, improvements in building efficiencies and conservation (e.g. window insulation, turning lights off that are not in use, energy efficient water heaters), are examples of factors that affect EI, or the amount of energy consumed for a given unit (product or service) of GDP. What the Kaya equation conveniently reveals is that a given percentage change in any of these variables will yield a corresponding percentage change in carbon emissions. Reductions or increases in any of these variables contribute to changes in carbon emissions.

Figure 4 shows that reductions in EI (in red) have contributed much more to reductions in carbon emissions than have changes in CI (in green). Of course, energy efficiency is not the only factor that can affect EI; Table 1 is from a RAND study that aggregates all of the factors that can influence EI.

[7] There are four terms: In order, they represent (1) Carbon Intensity of Energy (CI) [kilograms of energy-related CO2 per million BTUs], (2) Energy Intensity of the economy (EI) [thousand BTU's per dollar of GDP], (3) GDP per Capita or growth rate per capita [dollars per person], and (4) Population growth.

The product of the first two terms is called the Carbon Intensity of the Economy [kilograms of energy-related CO2 per dollar of GDP.

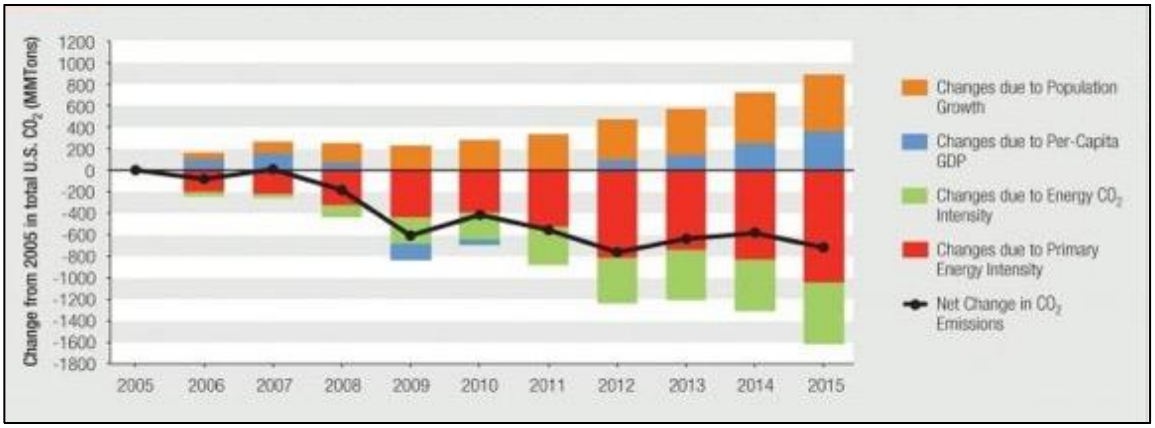


Figure 4: Changes in Total U.S. CO2 Emissions, 2005-2015 (IEA, 2016)

Table 1: Factors associated with Energy Intensity (Bernstein, Fonkych, Loeb, & Loughran, 2003)

Possible Factors Associated with Changes in Energy Intensity, by Energy-Consuming Sector

All Sectors	Industrial Sector	Commercial Sector	Residential Sector	Transportation Sector
Climate	Industrial mix	Number of buildings	Number of households	Passenger transit (mass versus individual transit)
Economic growth	Value of end products	Amount of floor space	Amount of floor space	Freight traffic
Price of energy	Capital turnover	Commercial sector mix	Number of household members	Automobile type and use
Energy efficiency	Capacity utilization	Employment levels	Income levels	Air traffic
Technological changes		New construction	Employment levels	
Government policies and actions		New energy-using devices	New energy using-devices	

Still, federal and state energy policies have tended to focus on the production side of the energy sector, both within the regulatory framework as well as with R&D

investments in technology. For instance, an NRC study calculated that the realized benefits to program costs from 1978-2000 was 83:1 for end-use technologies compared to just 7:1 for fossil-fuel energy-supply technologies (National Research Council (U.S.), 2001). Additionally, the DoE's first Quadrennial Technology Review of energy innovation concluded that the U.S. federal portfolio needed "rebalancing" toward end-use efficiency (US Department of Energy, 2011).

One of the primary tools that many states have implemented to transition away from hydrocarbon sources of energy is the renewable portfolio standard (RPS). This policy tool does account for a significant portion of the CI reductions in each state's portfolio. One study found that RPS compliance costs were less than 2% of average retail rates for most states and ranged from 0.1 to 3.8% among restructured markets yielding an RPS cost compliance between $2-$48/MWh (Heeter et al., 2014). A similar model for state-based standards for the energy efficiency, called Energy Efficiency Resource Standards (EERSs), are beginning to emerge across the U.S.

The Kaya equation is a reminder that energy efficiency is only a partial check on carbon emissions. Higher energy efficiency does not necessarily equate to lower overall energy demand. A growing population and increasing GDPs will continuously challenge policymakers in determining the scope and magnitude of public R&D investments, technologies, and regulations that will help limit global GHG emissions and reduce the impacts of climate change.

Energy Efficiency Policy Challenges

Energy efficiency itself does not have a consensus definition since efficiency can be thought of as a welfare characteristic and, thus, has differing meanings to different people. However, it is related to energy intensity, which is the ratio of energy consumption to some measure of demand for energy services. In this context, energy efficiency is when either energy inputs are reduced for a given level of service, or there are increased or enhanced services for a given amount of energy inputs ("Definition of Energy Efficiency," EIA).

Rebound Effects

One of the earliest criticisms of energy efficiency was put forward as early as 1865 by economist, William Jevons, who proposed that energy efficiency is counterproductive due to the "rebound effect" or "backfire". One of the corollaries states that individuals will simply use more energy as it becomes more efficiently consumed. For instance, someone buying a more fuel-efficient car will simply drive further because it is economically efficient to do so. Of course, the empirical evidence needed to make a quantitative assessment of all combined effects would be substantive. Some assess the macro-impact of backfire to be largely overstated (Gillingham, Rapson, & Wagner, 2015).

Rebound effects are categorized in two ways: 1) direct effects and 2) indirect effects. It is most common in the literature to refer to indirect rebound effects strictly as the positive income effect (due to less energy consumption) of all other goods (Gillingham et al., 2015). Thus, indirect effects are a function of how energy savings are spent on other goods and services and their respective energy intensities. Similarly, the direct rebound effect is defined as the change in energy usage resulting from the combined substitution and income effects on the demand for the energy-efficient product. In addressing direct effects, a review of short and medium run elasticities of demand for gasoline and electricity fall in a range between -0.05 to -0.4. Similar studies in developing countries, although less rigorous in their analyses, show similar ranges, -0.1 to -0.4 (Gillingham et al., 2015). Two notable areas are underrepresented in many of these studies, 1) commercial and industrial usage, and 2) non-gasoline or non-electricity consumption (e.g. natural gas-heated hot water heaters).

Another important differentiator of energy efficiency improvements is whether they are a result of technological "zero cost breakthroughs" (ZCB), or are part of a command-and-control regulatory policy that is not costless for producers, sometimes referred to as "policy-induced improvements" (PIIs). Several researchers have discussed the advantages of implementing pigovian taxes over efficiency standards and regulations (Linares & Labandeira, 2010).[8] In general, ZCB type changes tend to be easier to measure and quantify as the set of variables that need to be controlled substantially shrink, making it more conducive to standard quantitative economic techniques.

Behavioral economics does play a role in understanding the magnitude and direction of rebound effects, but energy-minimization should not be confused with welfare-maximization.

[8] Some theories have been offered that suggest that under certain conditions, Pigovian taxes coupled with an energy efficiency standard can yield higher welfare than a Pigovian tax alone (Tsvetanov, Segerson, & others, 2011).

Government Response

Public policy response to the energy efficiency gap remains widely varied. One of the most enduring responses has been to mandate industry to simply build more energy efficient products regardless of customer choices. Although largely motivated by responses to the security of supply concerns in the 1970's and the recognition that greenhouse gases (GHGs) are an "air pollutant" under the Clean Air Act, the Corporate Average Fuel Economy (CAFÉ) standard provides a command-and-control approach. Other programs, such as Energy Star, provide incentives to manufacturers by leveraging labeling strategies to assist in customer efficiency choices.

Various other policy tools have been implemented by states to address the gap. Below is a sample, but non-exhaustive, list.

Energy Efficiency Resource Standards (EERS) and State Mandates

This policy tool, similar to supply-side Renewable Portfolio Standards (RPSs), are mandates used by states to encourage energy efficiency by establishing energy savings targets for utilities (25 states are currently implementing electricity EERSs[9] (see Figure 5). They require utilities to procure a percentage of their future electricity needs using energy efficiency (EE) measures (York, Witte, Nowak, & Kushler, 2012). States adopt EERS policies for several reasons, including for environmental reasons, peak load reduction, *consumer energy efficiency behavior limitations* (or failures), economic development, energy security, or some combination of these (Brennan & Palmer, 2012). Forty-four states (and D.C.) have some sort of ratepayer-funded energy efficiency

[9] Of these, 15 also have EERS policies in place for natural gas.

programs, although not all are part of an EERS system (ACEEE). An EERS targets electricity or natural gas savings through market-based trading systems. In some cases, EERS can be used to meet RPSs. The average mandated energy efficiency savings among the states with binding policies is around 11.5 percent of total electricity load (Palmer, Grausz, Beasley, & Brennan, 2013). Consistent with the theme of this section, the structure of EERSs vary greatly between states. For instance, some requirements are in percentage of total sales, percentage of load growth, and absolute energy savings. Within these requirements, some used a fixed reference year of energy usage, while others use a rolling measure over a number of years.

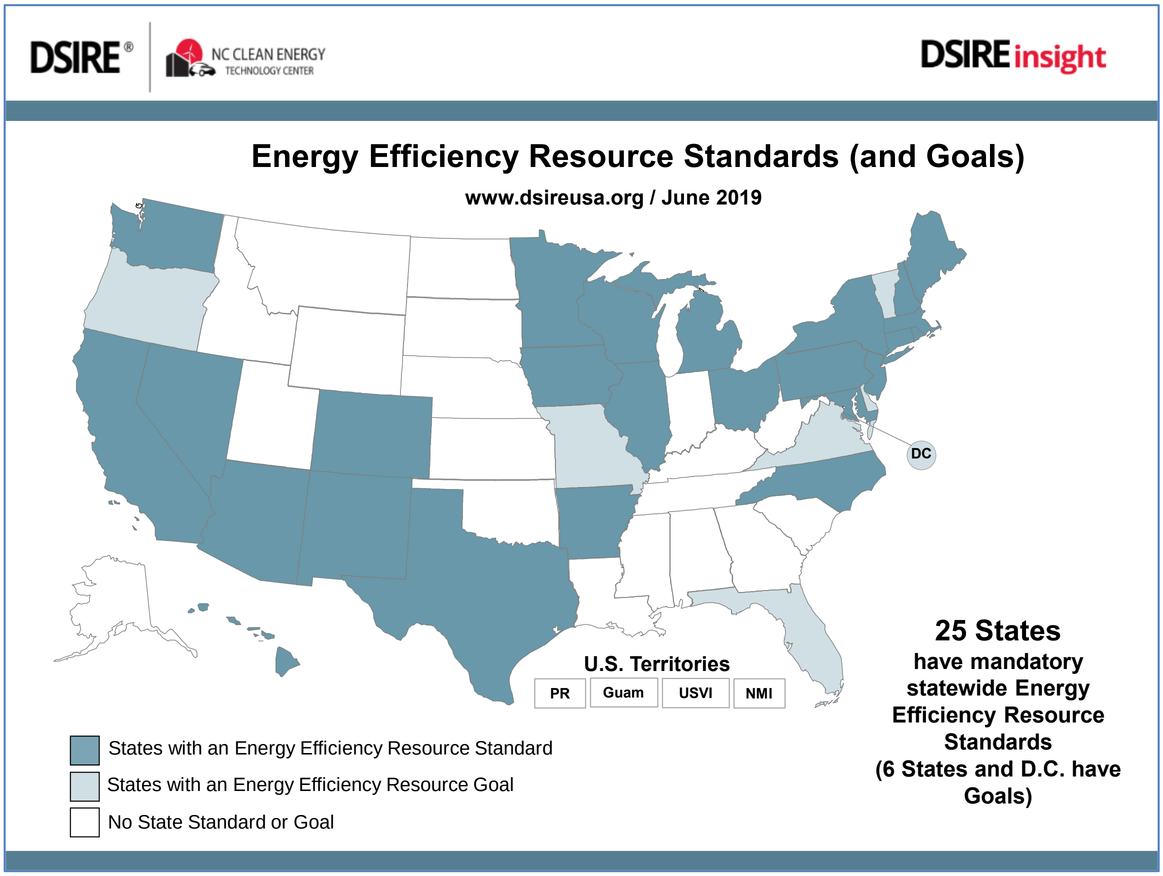


Figure 5: Energy Efficiency Resource Standards (and Goals)

Although not mandatory standards like EERS's, integrated resource planning (IRP) mandates require utilities to consider and incorporate energy efficiency and conservation options prior to approving requests for new generation sources. Additionally, many IRP statutes require PUCs to evaluate the indirect costs of environmental damages, including climate change, illnesses, and agricultural damage (Eisen et al., 2015, pp. 888–889). One of the challenges to IRPs, many of which were written in the early 1990s, is to remain current in the face of widespread restructuring and regionalization of utility markets.

Subsidies

Few energy policy topics get more attention than subsidies, defined as a transfer of resources from government to a public or private entity, with the goal of lowering the cost of some good or service and thereby increasing its production or consumption, or to enable a firm to increase revenues and/or decrease costs (Geri & McNabb, 2011, p. 82). The policy goal of subsidies is to incentivize consumers who would not otherwise make those investments. Subsidies can take various forms, including tax policy, direct government spending (e.g. R&D), loans, access to federal lands, including royalty provisions, tariffs, insurance, audits and preferences to certain public projects.

Subsidies suffer from problems of inframarginal consumers, better known as free riders. Because subsidies must be funded, they often are the target of distortionary taxes, which are economically inefficient and often politically challenging. One German study found that 92 percent of one residential energy improvement subsidy program went to consumers who would have made those improvements without the subsidy (Grösche, Schmidt, & Vance, 2009a). Subsidies for energy efficiency can also suffer from a general lack of knowledge of demand elasticities for durable goods (Allcott, 2011), or because adopters of energy efficiency subsidies are more informed and attentive to energy costs than non-adopters (Allcott, Knittel, & Taubinsky, 2015).

Even given these limitations on subsidy efficiencies, the focus on supply-side management dominates the energy sector. One study shows the contrast with the level of subsidies to energy-supply technologies, which have outstripped end-use subsidies by a ratio of 35:1 (Sovacool, 2009).

However, it is useful to examine the effects of DSM subsidies that have targeted behavioral anomalies, either in full or in part. Whereas free ridership is the liability of subsidies, *free drivers* are often the target of DSM and other energy subsidies, those who make a purchase because their awareness was raised by the existence of the subsidy (Geller & Attali, 2005).

Public utility regulators (PUCs) oversee utility implementation of energy efficiency mandates. The bulk of utility spending on energy efficiency programs goes toward subsidies, commonly in the form of home and business energy audits, energy-efficient lightbulbs, and rebates for energy-efficient (e.g. ENERGY STAR-certified) durable goods, including appliances, water heaters, and HVAC systems. These programs are favored by regulators because new technologies make it easy to quantify the energy efficiency improvements. Inefficiencies due to free ridership, however, are commonly not evaluated.

Demand Side Management (DSM) Incentives

DSM is an umbrella term for programs that are aimed at reducing energy consumption and/or moving demand to minimize the difference between peak and off-peak consumption. Closely linked with the movement toward utility restructuring in the 1970s was a growing frustration by consumers of a seemingly endless pathway toward higher utility rates, partly spurred by an influx of expensive nuclear power. Unusual partners in this movement were environmental groups who were fearful of dangerous emissions from fossil fuel generators, particularly coal. As a result utilities began to invest in programs aimed at reducing electricity demand (Eisen et al., 2015, p. 889).

Utility spending on DSM peaked in the early 1990s. The reason the trend was halted is largely attributed to concerns amongst utilities that under new restructuring regulations (aka deregulation) that were aimed at increasing competition, they would place themselves at a competitive disadvantage without guaranteed rate recovery mechanisms as a backstop (Arimura, Li, Newell, & Palmer, 2011).

Experimentation with deregulation, or restructuring, in the U.S. has had mixed success, but with several glaring failures such as occurred in California in 2000-2001. This "quasi-deregulation" strategy may, in effect, have highlighted the worst aspects of competitive and regulatory policies. Regardless, it certainly only addressed one side of the marketplace, the supply side. This approach might be expected in view of historic ratemaking methodologies that incentivize utilities to sell more electricity because increased revenues lead to increased profits. This model goes back to the earliest days of the electricity utility industry, when Samuel Insull encouraged government intervention in ratemaking in order to eliminate competition in the 1920's and 30's.

Partially because of energy efficiency and other DSM programs utility revenues have decreased due to less demand, placing burdens on utility companies, especially investor-owned utilities (IOUs), to recover stranded costs from non-DSM users. In other words, many of the operational benefits of DSM are not being offset efficiently among utility consumers. Federal legislation (incl. PURPA and EPAct 1992) specifically encouraged public utility commissions (PUCs) to structure rate recovery mechanisms that encouraged utility companies to make investments in programs that reduced demand and improved efficiency. Still, the pressure to impose fixed charges on DSM users is often opposed by those who wish to develop new technologies, many of which are designed to promote customer behavior change.

Section 1301 of the EISA 2007 established the national policy for grid modernization, stating the goals and technology objectives of the Smart Grid[10], the moniker for a wide range of infrastructure and application upgrades to the electric grid. To date, the regulatory excursions into DSM to support these objectives have been incremental and uneven, although FERC appears committed to the benefits of DR[11]. Another constraint is the uneven deployment of "smart" technologies, such as Advanced Metering Infrastructure (AMI) (better known as smart meters), which incorporate bi-directional communications between consumer and utility. This technology and associated standards enable dynamic pricing structures to be deployed as well as real-time measurement of consumption data. By the end of 2016, over 70 million smart meters had been installed in residences and over 6 million in commercial buildings, for a total

10 It is the policy of the United States to support the modernization of the Nation's electricity transmission and distribution system to maintain a reliable and secure electricity infrastructure that can meet future demand growth and to achieve each of the following, which together characterize a Smart Grid: (1) Increased use of digital information and controls technology to improve reliability, security, and efficiency of the electric grid. (2) Dynamic optimization of grid operations and resources, with full cyber- security. (3) Deployment and integration of distributed resources and generation, including renewable resources. (4) Development and incorporation of demand response, demand-side resources, and energy-efficiency resources.
(5) Deployment of `smart' technologies (real-time, automated, interactive technologies that optimize the physical operation of appliances and consumer devices) for metering, communications concerning grid operations and status, and distribution automation. (6) Integration of `smart' appliances and consumer devices. (7) Deployment and integration of advanced electricity storage and peak-shaving technologies, including plug-in electric and hybrid electric vehicles, and thermal- storage air conditioning. (8) Provision to consumers of timely information and control options. (9) Development of standards for communication and interoperability of appliances and equipment connected to the electric grid, including the infrastructure serving the grid. (10) Identification and lowering of unreasonable or unnecessary barriers to adoption of smart grid technologies, practices, and services. (Energy Independence and Security Act of 2007 - SEC. 1301)

11 Former FERC Chairman, Jon Wellingham, called DR a "killer app" ("Demand More | Tangent Energy Solutions,")

penetration rate of 46.8 percent[12] (Foster, Burns, Kathan, Lee, & Peirovi, 2018). Other tools of DSM include distributed energy resources (DER), energy storage devices, and intermittent renewable energy resources.

Demand Response

One the primary tools of DSM is demand response (DR), defined by FERC as "changes in electric use by demand side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times at high wholesale market prices or when system reliability is jeopardized" ("FERC: A National Assessment & Action Plan on Demand Response Potential"). This DSM policy tool is important to examine given the relatively large penetration it has in the electricity sector. Accordingly, it offers insights to how programs aimed to reduce total demand (vice shifting load) might be structured. DR programs fall into three major categories: 1) organized (dispatchable) wholesale markets, 2) load management or control, and 3) price-mediated, or time-varying rates.

The proponents of DR in the electricity sector make a two-fold argument: 1) reducing demand during peak periods can provide a check against increasing marginal costs of generation (often becoming exponential during very short periods) (see Figure 6), 2) reducing demand during peak periods obviates the need for peaking plants, some of which operate for fewer than 100 hours per year. This can have both environmental

[12] Over 16 million smart meters were funded through the American Recovery and Reinvestment Act (ARRA) of 2009 alone ("Advanced Metering Infrastructure and Customer Systems | SmartGrid.gov," n.d.) ("Advanced Metering Infrastructure and Customer Systems | SmartGrid.gov," n.d.) ("Advanced Metering Infrastructure and Customer Systems | SmartGrid.gov," n.d.) .

benefits, as these plants are typically fossil fuel generating units, as well as economic, since this reduces the total capital expenditure required to meet demand.

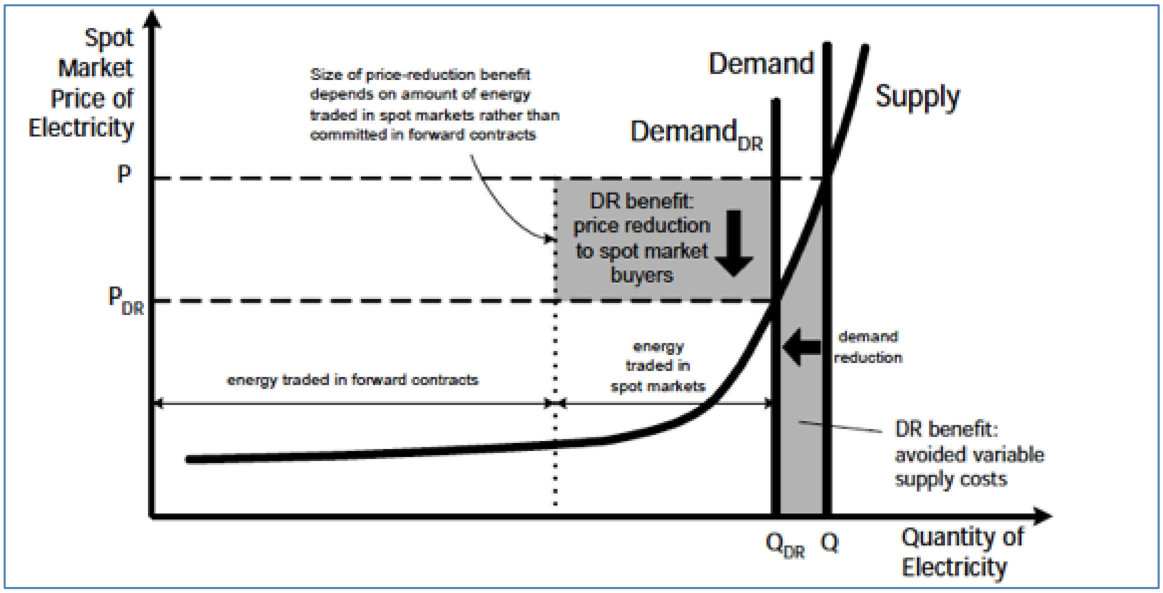


Figure 6: Impact of Demand Response in Wholesale Spot Markets (QDR, 2006)

It is important to note that DR, unlike some other aspects of DSM, are *not designed necessarily to curtail overall energy usage*, but rather to optimize the efficient deployment of energy generation resources. Consequently, it has the potential to improve energy intensity without necessarily reducing consumption. There is debate about the conservation aspects of DR, where some argue that it only time shifts peak use. Clearly, in instances where customers allow a load (e.g. water heater or heat pump) to be controlled during peak demand, there will limited capacity to “recover” for the inconvenience. In other words, DR as a conservation tool is not a primary objective. Still, it serves as an important DSM tool that can provide behavioral insights that are applicable to other energy efficiency and curtailment behaviors. Pay-for-performance (P4P) programs, for example, will provide much better insights into how consumers respond to incentives that extend beyond the asynchronous, short time periods associated with DR.

DR programs lag behind funding for subsidy/rebate programs within the utility industry. However, the technology that makes DR effective as a DSM tool has great potential for incentivizing energy conservation. Much of this is powered by smart grid technology and improved, targeted communication with customers.

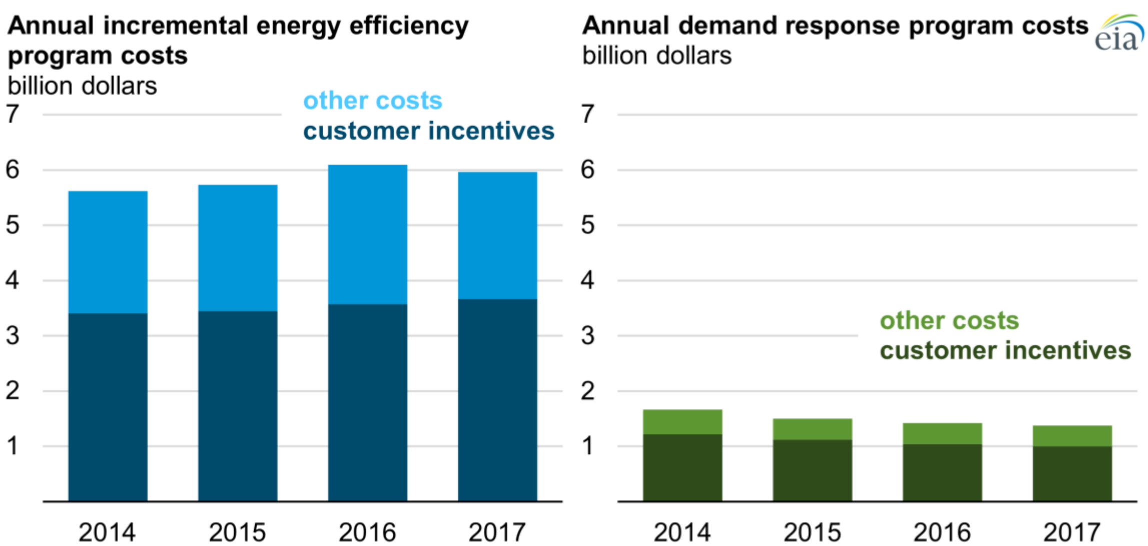


Figure 7: Comparison of Utility Spending on Energy Efficiency and Demand Response Programs (Energy Information Administration, 2019)

<u>Organized Wholesale Markets</u>

On a volumetric (equivalent MW) basis, wholesale demand response (DR) markets have had the greatest impact of the three primary DR categories. Until recently, these have generally been limited to commercial and industrial customers but are now incorporating residential customers into the mix. Regional electricity wholesale markets, such as PJM and MISO, are increasingly using DR as dispatchable resources. Instead of calling upon additional generation capacity to meet overall system demand, RTOs and ISOs are using "curtailment service providers" or "aggregators", acting as intermediaries between customers and electricity dispatchers (Eisen et al., 2015, p. 921). FERC's primary instruments to date for promoting DR are Orders 719 and 745. The first order requires RTOs/ISOs to permit aggregators to bid DR on behalf of retail customers directly into the wholesale energy markets while the latter order requires those bids to be paid full market prices (Eisen, 2013). Overturning an earlier D.C. Circuit decision, SCOTUS recently affirmed FERC's Order 745 governing wholesale demand response, stating that it was within their Federal Power Act (FPA) authority to charge wholesale rates[13] "with room to spare". Given the wide discretion that the Court gave in FERC's ability to integrate various "non-traditional" tools of meeting supply and demand, some have called this among the most significant energy law cases of all time (Review, 2016).

These markets take the form of 1) capacity, 2) energy, and 3) ancillary services. The first two have analogs on the supply side, the maximum *capacity* for curtailment and the total *actual* curtailment (supply). Participating customers receive payments for being on stand-by (capacity market) and sometimes an additional amount for actually curtailing

[13] specifically, to charge locational marginal price (LMP)….without a further "penalty" for what load-serving entities (LSEs) must then accommodate (e.g. their inability to sell more electricity). In effect, it puts wholesale DR bids on par with wholesale generation sources.

use (energy market). Figure 8 shows the range of DR penetration throughout the RTO/ISO regions that have wholesale markets.

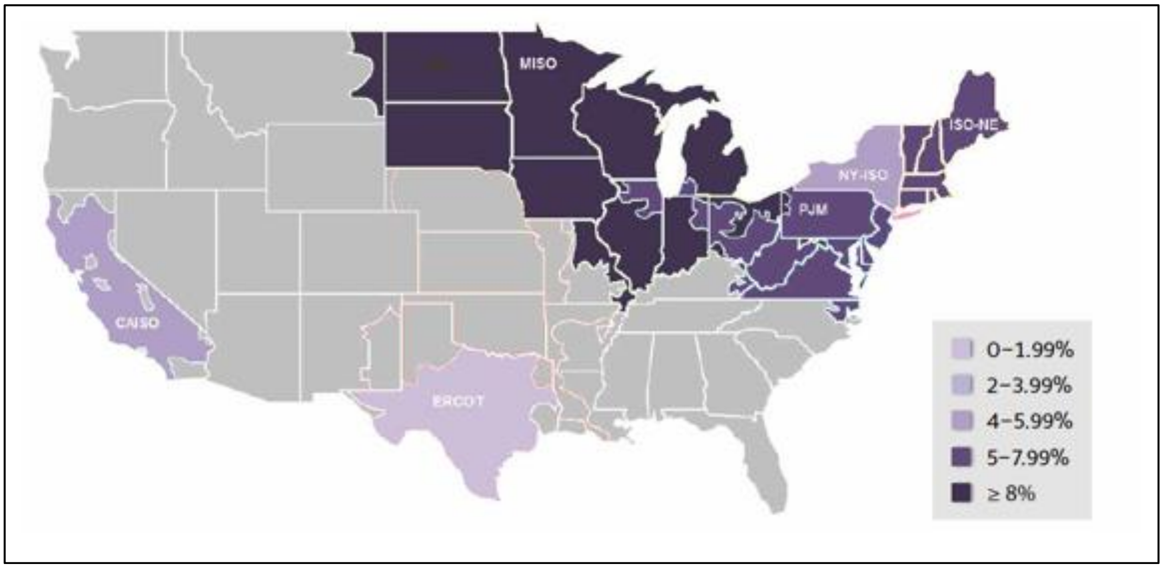


Figure 8: Demand Response Saturation as a Percentage of Total RTO/ISO demand (Managan, 2014)

Load Management and Control

Although more widely implemented geographically than wholesale exchanges, including by many regulated utility providers, load management and control still encompasses a relatively small share of DR avoided load. In fact, many DR aggregators use load management as a tool for wholesale exchanges. Typically, these programs are managed by the load serving entity (LSE) and often involves the installation of a controllable device onto a load (such as for a hot water heater, a heat pump, or thermostat) in exchange for compensation to the customer. Many of these programs are part of distributed energy resource (DER) programs that help balance the power demand throughout a service region. This is common for hot water heaters which can act as a virtual battery, increasing temperature when demand is low.

Time Varying Rates

Time-varying rates are certainly not a new concept, especially in non-regulated or deregulated industries. Air travel, hotels, car rentals, movie theaters, and toll roads are all examples of services where price variation responds to demand. Although not yet supported by empirical data, there are some who theorize that, because electricity prices are time-invariant and do not reflect actual real time costs, they are injecting a distortion that places prices below marginal costs and, therefore, may be lowering the demand for energy efficiency (Brennan, 2010).

Time-varying rates encompass a host of methods that allow electricity rates to vary throughout the day, season, or at unpredictable moments when demand rises above a threshold. For residential and small commercial customers these types of rates require remote metering technology, generally through AMIs. Although the specifics of individual time-varying rates differ, they all share characteristics that are designed to: 1) use price signals to inform customers that shifting loads during high demand can result in cost savings; 2) lower the total production capacity by flattening the demand curve. This flatter profile requires fewer generating facilities, thus reducing the demand for "peaker plants" that typically only operate a few hours a year. The decreased capital costs of production can be passed on to *all* consumers; 3) moderate wholesale market prices during peak hours; 4) encourage deployment of distributed resources, such as rooftop solar (Cappers, 2011). This is because during peak demand, time-varying solar power is also typically operating at maximum efficiency. Also, electric vehicle charging from/discharging to the grid can effectively help flatten the demand curve.

Time-varying rates include 1) time-of-use (TOU), 2) Critical peak pricing (CPP), 3) Peak Time Rebates (PTR), and 4) real time, or dynamic, pricing (RTP). TOU prices and time periods are fixed at least a year in advance. CPP and PTR rates identify the highest 60-100 hours of demand in a year and signal those periods a day ahead of time to consumers. Peak/off-peak pricing is the most common practice used among utility companies to incentivize consumers to use less energy during periods of highest demand. For the CPP case, customers are charged a significantly higher rate during peak demand periods –or- credited with a rebate for the PTR case. Lastly, there is RTP whereby electricity rates are changing constantly, an hour ahead of implementation.

There are policy challenges to implementing time-varying rates; for instance: 1) fixed, or near fixed, rates protect consumers from the "costs" of monitoring rate changes. This can be thought of as the cost of paying attention; 2) the infrastructure costs of information sharing, or ensuring that current rates are transparent and trustworthy, and thus preventing arbitrage, and 3) equity concerns that savings are not disproportionately benefiting a particular demographic. Still, despite these constraints, most economists believe that real time pricing would lower the overall *average* wholesale cost of power, which would result in lower prices for consumers (Borenstein, 2002).

The empirical results of time varying pricing programs vary but do support the theory that peak demand can be reduced while the inherent savings can be passed on to consumption at non-peak time periods. The most comprehensive study to date looked at

109 programs that incorporated either TOU, CPP, PTR, or RTP and included a customer base from less than a hundred to several tens of thousands (Faruqui, Hledik, Ryan, & Palmer, Jennifer, 2012) (see Figure 9). Higher peak to off-peak price ratios yielded larger peak reductions, but at a decreasing rate (see Figure 10). Major sources of variation included, pilot design, price signal, central-air conditioning density, presence of enabling technology (e.g. programmable thermostats, In-home displays, and load switches), weather, sociodemographic factors, and marketing. Subsequent studies using TOU pricing and programmable communicating thermostats (PCTs) that automatically respond to price changes achieved peak to off-peak changes of up to 48 percent, but with variation among demographics, weather and across usage distribution (Harding & Lamarche, 2016).

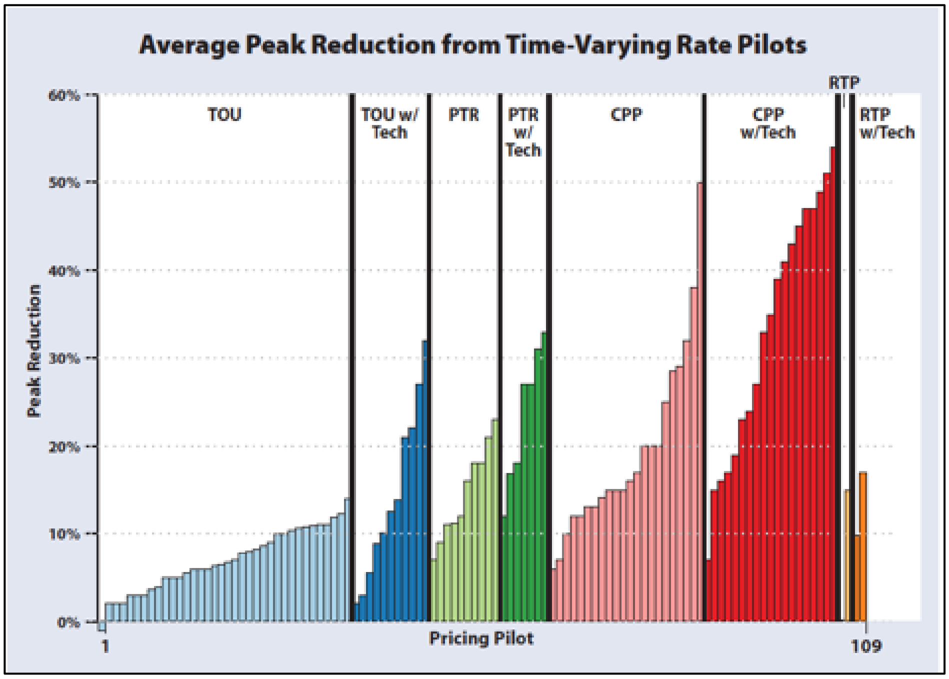


Figure 9: Average Peak Reduction from Various Time-Varying Rate Pilot Studies (Faruqui et al., 2012)

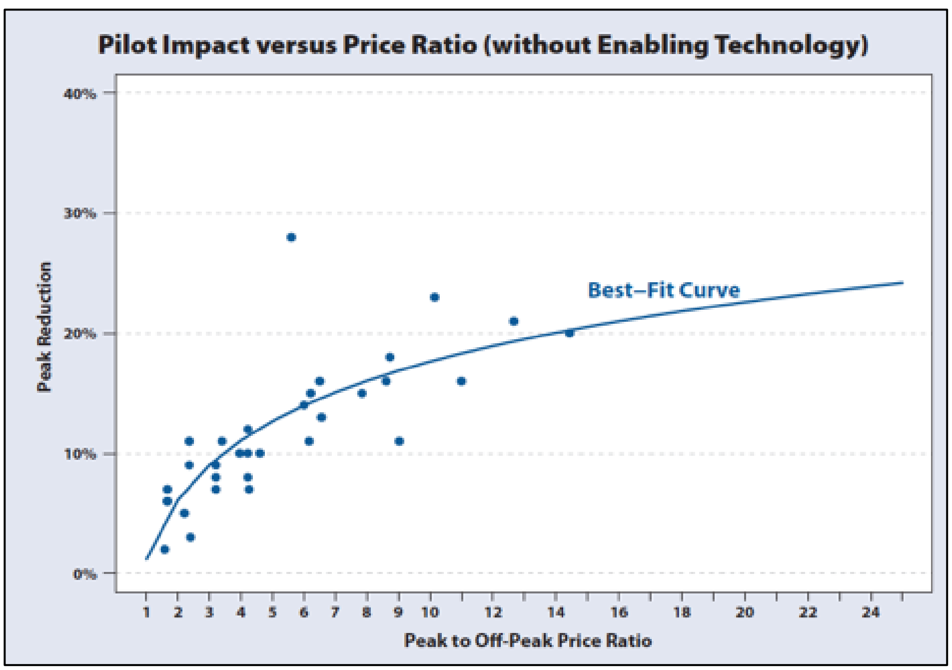


Figure 10: Peak Reduction as a Function of Peak to Off-Peak Price Ratio (Faruqui et al., 2012)

Other potential benefits are more ambiguous. For instance, it is unclear whether there is conservation associated with time-variant rates; load shifting is a term whereby consumers simply shift the load from on-peak to off-peak hours. The extent to which consumers load shift also seems to vary among the population (Harding & Lamarche, 2016). Also, there are instances where environmental impacts are positive depending on the generating resource mix. This is because peaker plants are typically less efficient and have higher rates of carbon emissions. One study found that the result of load shifting could result anywhere from a 0.9 percent decrease or as high as a 0.3 increase in GHG emissions (Hledik, 2009).

As mentioned earlier, one prospective policy challenge to using time varying rates is that they are non-equitable; that is, it may only benefit those who have the ability to shift consumption habits based on price signals. First, it is important to understand that under the common flat pricing schemes, users during peak demand period are, in effect, being subsidized by users who consume more energy during non-peak times. This inequity is, perhaps, so baked into the inertia of current regulatory policy that it often is overlooked. Consequently, there is likely no Pareto-efficient manner to adjust for the current cross-subsidization and, therefore, peak consumers would potentially find themselves paying more under a variable pricing scheme. Nevertheless, the multi-pilot review found that because low-income customers tend to have flatter load shapes, almost two-thirds (65 percent) were better off on a CPP rate than on a flat rate. Also, overall increases versus decreases in bill changes were fairly even (Faruqui et al., 2012).

Other Energy Efficiency Programs

Financial incentives other than subsidies and DR programs have effectively been used in demand-side management (DSM) to encourage users to reduce consumption. The incentive is behavior neutral in that the reduced consumption can result from either efficiency or curtailment behavior. The most comprehensive studies for residential households in the energy sector are quite dated. Over a period of eight weeks, households who had received a high reward ($0.30 for each 1 percent reduction in weekly kWh consumption = 240 percent rebate), feedback and information reduced electricity use by about 12%. A low rebate system was only marginally effective, and weekly feedback and information were ineffective in curtailing electricity use (Winett, Kagel, Battalio, & Winkler, 1978). This research uses this framework, called pay-for-performance (P4P), as a control. It is noteworthy that very little empirical evidence exists for this framework.

Another study investigated the combined effect of information, prompts (reminders), biweekly feedback (about the performance of the entire group) and rewards (100% of the value of electricity savings). All participants received the same combination of interventions. The intervention lasted 14 weeks and resulted in average savings of 6.2% relative to baseline. The effects appeared to be strongest immediately following implementation of the intervention (Slavin, Wodarski, & Blackburn, 1981). A second study was set up along the same lines, but instead, participants now received 50% of the monetary value of electricity savings, and a bonus amount was given if total group savings exceeded 10% (a cooperation game intervention). The combination of interventions resulted in electricity savings of 6.9%.

Financial incentives for proven energy reductions present several advantages over other types of subsidies. First, offering a subsidy for an energy efficient product does not guarantee that product will get installed correctly and placed in service. Additionally, rewarding actual energy reductions addresses the problem of rebound effects. This may be even more effective for residential households since, unlike businesses, growth in energy demand is not closely linked to productivity.

By far the most widespread behavioral-based energy efficiency program remains the home energy report (HER) [Usage Feedback and Social Comparison]. It is also one of the oldest, reflecting the slow pace of change in the residential energy efficiency sector. Utility spending on all residential behavioral programs made up only 2 percent of their DSM portfolio while returning 10 percent of average DSM portfolio savings ("Home Energy Reports," 2019). Utility spending on energy efficiency is minute, consisting of less than one percent of retail sales in most states (Figure 11). The average utility company's incremental spending per customer on energy efficiency varies wildly among states, ranging from $0 (Alaska) to $128 (Massachusetts) ("State efficiency incentives averaged $24 per customer, ranged from $0 to $128 in 2016—Today in Energy—U.S. Energy Information Administration (EIA)," 2018). Typically, these programs are a response to mandates by state legislators, reflecting the continuing challenge to incent utility companies with rate-based models that favor fixed costs.

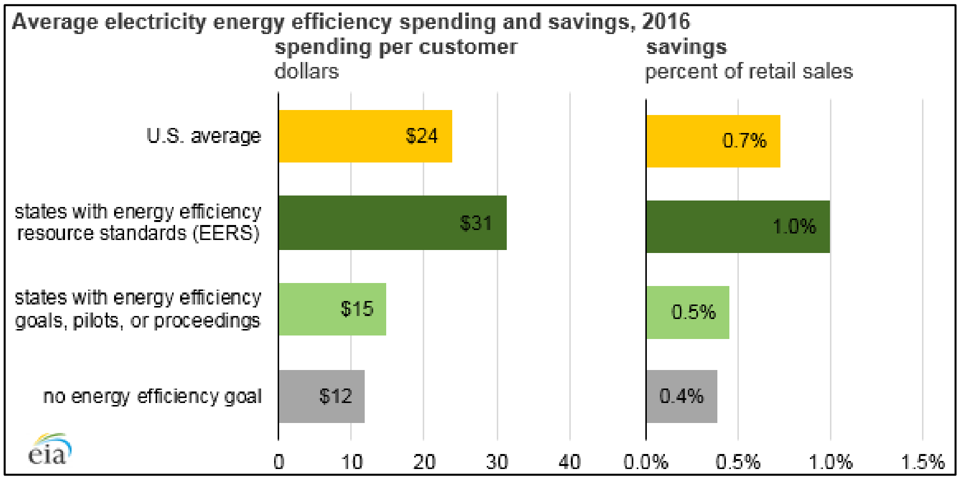


Figure 11: Utility spending on Energy Efficiency Programs

Emerging technologies offer new opportunities to test energy efficiency incentives. With the widespread implementation of smart meters, consumer usage can be collected at short intervals, allowing for sharing of real-time energy usage and creating opportunities for innovative new techniques for changing user behavior. Today, utility companies are able to use household smart meter data to help reduce peak demand consumption through customer engagement. As mentioned earlier, the specific programs vary widely, including both financial and non-financial incentives. The following discuss other ways that real-time energy feedback, enabled by smart metering, are being integrated into energy efficiency programs.

Pay for Performance (P4P)

These programs have been around for decades to encourage customers to reduce energy consumption. The concept is to reward consumers for *actual* reductions in energy consumptions, versus programs (e.g. rebates) that simply reward purchasing of energy efficient equipment. These types of programs are generally structured in one of three ways: 1) performance target incentives, 2) shared savings incentives, and 3) rate of return incentives ("Incentivizing Utility-Led Efficiency Programs: Performance Incentives | ACEEE").

To date, P4P programs have targeted commercial and industrial customers with utility companies working through aggregators, or energy service companies (ESCOs), who help private businesses manage project finances. This makes sense, since ESCOs are highly informed about energy efficiency technologies and many industries have complex energy systems. Consequently, few P4P programs have attracted interest from individual customers. For instance, the U.S. residential household sector has not yet been offered a utility-scale P4P program[14]. This is somewhat surprising considering the success of other demand-side management (DSM) programs, such as demand response (DR), which aim to curtail usage during peak demand. In fact, residential housing represents a high percentage of all structures that are metered and, thus, easy to establish usage baselines, a condition the National Resource Defense Council (NRDC) recently suggested was highly attractive for P4P programs (Borgeson, 2017).

One of the natural benefits of P4P programs is that rate structures should, theoretically, be much simpler than for DR programs. Whereas, DR programs attempt to target short, and sometimes hard-to-predict, events throughout the year, P4P rate structures need not be time dependent. Again, this is because the goal is to reduce overall demand, not shifting away from peak usage periods.

[14] Pacific Gas and Electric Company (PG&E) recently announced the U.S.'s first residential P4P program, called "Cool Savers". (Orvel, 2019)

Prepay as an Energy Efficiency Program

There is some evidence that suggests that prepayment of electricity could reduce consumption in residential households. This is very common outside of the U.S. with substantial percentages of the population using prepay in Africa, Europe, South America, and Asia. The research is very light in this area, especially in the U.S., with some challenging the notion that prepay should even be called an energy efficiency program. Some estimates suggest that in Minnesota prepay participants could reduce consumptions between 2 percent and 8.5 percent, with the former including provisions for automatic shutoff. However, utility regulators have been slow to adopt prepay due to concerns regarding consumer protection (Sussman, LeZaks, Drehobl, Kushler, & Gilleo, 2018).

In many ways this program most closely resembles the EEE framework created and tested by this research. This is true in two key respects, 1) there is an element of loss that takes place as energy is consumed, and 2) feedback is a key element in leveraging behavioral change. Loss aversion in prepay programs is quite literally the aversion to having electricity disconnected. Prepay also requires the outlaying of actual credit/cash as opposed to the paying after consumption. This may help minimize Time-inconsistent Preferences and Hyperbolic Discounting which is quite prevalent in the decision to purchase energy efficient products.

THE ENERGY EFFICIENCY ESCROW (EEE) AND PAY-FOR-PERFORMANCE (P4P) FRAMEWORK

This research introduces a framework that seeks to explore if, and how, disparate theories of behavior can be activated within the energy efficiency sector. The concept of the energy efficiency escrow (EEE) is drawn from an idea most closely associated with the real estate industry. An escrow account is nothing more than a holding tank. In mortgage transactions it is a vehicle used between buyers and sellers. Mortgage lenders also use it to pay property taxes and insurance on behalf of the homeowner. The key characteristics of the escrow are: 1) they exist for a single purpose, 2) the value within the account is real, and 3) they cannot be accessed by the beneficiary until certain conditions are met.

Escrows may have the potential to address bounded rationality challenges and reduce time inconsistencies in the energy efficiency sector. For instance, a cost-effective incentive that may appear to be small based on the conversion, say $0.05/kWh, does not immediately instill potential cost savings to a consumer. If the potential savings can be conveyed in gains that are significant enough, this could make it worthwhile for the consumer to pay attention. Applying a rate-based incentive over a long period of time can also help eliminate cognitive errors that consumers make in calculating long-term savings. This is the same basic principal used in many labeling techniques used for durable goods, such as washing machines, dishwashers, and other household appliances.

This is also a common technique used for sharing what the fuel costs will be over the lifetime of a new vehicle.

Since escrows hold real value to the beneficiary, loss aversion can be a potential behavioral trait that is activated. At its core, prospect theory suggests that people dislike losses more than they like an equivalent gain. In other words, they get more disutility from losing something they own, than utility in gaining something they do not. Escrows provide a way of reflecting losses and, therefore, disutility throughout the period of performance. The EEE is, in fact, an endowment, which creates immediate stored wealth that can only be reduced. The rate of reduction is determined by the behavior of the beneficiary. Because individuals tend to overvalue things they already own, we might expect their personal cost/behavior to reflect that belief.

The EEE framework addresses the heart of loss aversion, "the aggravation that one experiences in losing a sum of money appears to be greater than the pleasure associated with gaining the same amount" (Kahneman & Tversky, 1979, p. 279). In the case of the EEE framework, the "cost" to consumers includes paying attention and actually reducing energy use. Additionally, the EEE can be decoupled from individual risk aversion preferences, which are sometimes comingled in loss aversion studies, since any potential losses are entirely within the individual's control.

Figure 12 suggests how a consumer might respond to the same incentive given two different frameworks. Suppose the incentive is that 5 cents will be given to a consumer if, over the next hour, they use 1 less kW of power (or 1 kWh). There exists a maximum of 5 cents at stake. Prospect theory suggests the disutility (-40) of losing the 5 cents is greater than the utility (16) of gaining 5 cents despite achieving the same financial outcome. Simply be moving the reference point, an EEE induces 40 units of disutility that can be avoided.

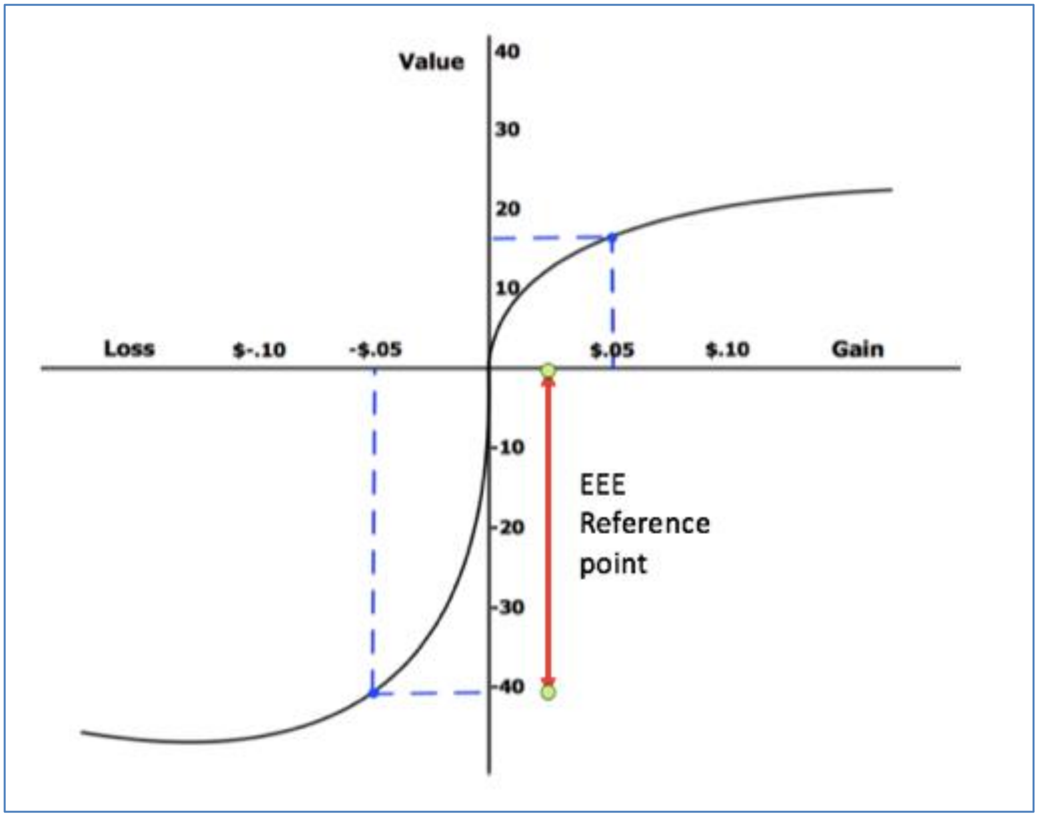


Figure 12: Potential Disutility Induced by EEE

It is worth noting the slope of the curve in the 3rd quadrant. This suggests that as the value of the endowment increases the rate of disutility experienced decreases. For instance, a $5 loss from a $40 endowment will create less disutility than a $5 loss from a $10 endowment. This might suggest several responses from an EEE, 1) non-linear effects as EEE's approach depletion, and 2) fewer beneficial outcomes with large initial EEE balances.

One seminal difference of the EEE vs. P4P framework from most loss aversion studies is that the potential gains in a P4P program are notional and cannot be quantified a priori. For instance, at the beginning of the treatment period all of the participants in the treatment group (EEE) know exactly how much they can potentially lose, whereas in the control group (P4P) the potential gains are speculative. With a few simple calculations, this is certainly discoverable, but not made explicit. This research design avoided any projections of potential gains to the P4P group in order to minimize triggering loss aversion anxiety. For instance, a periodic report such as, "at this rate of energy usage, your reward would be X dollars at the end of the incentive period", may itself be interpreted as something to be lost.

The P4P group in this study is a notional construct that mirrors the efforts of some utility companies to provide a rate-based incentive to reduce energy consumption. The reason it is called notional is because there is no empirical evidence that shows how consumers will respond to a real-time, rate-based incentive for energy conservation. Continuous usage feedback combined with a baseline usage reminder is an added feature provided to both groups in this research that differentiates this from previous studies. However, some of the behavioral change that the P4P user makes is based on risk mitigation, or a heuristic calculation based on how close the user believes they are conserving in order to maximize utility, financial or otherwise. For this group, there are neither any reminders about what financial gains are at stake nor any forecasting about how much of their potential gain they have forfeited through use.

The EEE user, on the other hand, is balancing loss aversion based on a value that is explicit, where no heuristics are required, but also has the ability to monitor the same feedback mechanisms, historic and baseline energy usage, provided to the P4P group.

Lastly, both the P4P and EEE frameworks attempt to address some of the criticisms of feedback systems in general. One researcher identified several liabilities in coupling IHDs and financial incentives, 1) rewards should be delivered soon after behavior changes, and 2) most IHDs do not help with the “tricky cognitive problem” of making sense of consumption decisions (Buchanan et al., 2015). Both the P4P and EEE framework attempt to address the first directly, while the EEE framework targets the second directly. Another liability not addressed in this research is allowing users to use non-pecuniary incentives, such as explicit, pro-environmental information, in parallel with financial incentives because “a one size fits all approach for IHD cannot be justified” (Dam et al., 2010). This is encouraged for further research.

Figure 13 shows a mapping of the different theories of behavior that shape the two groups.

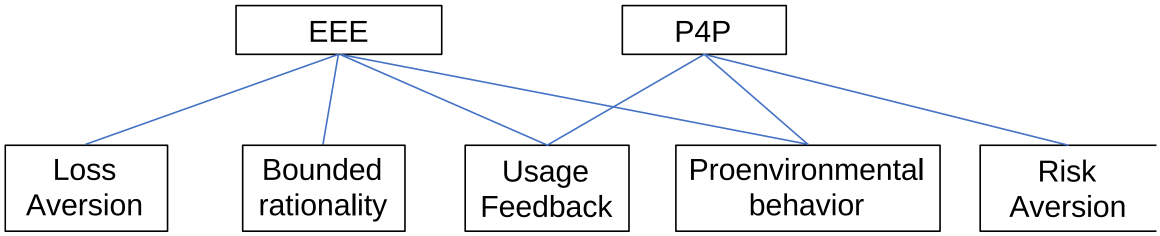


Figure 13: Mapping of Experiment Frameworks to Theories of Behavior

The GOEFER app will ensure that all users have real-time access to their individual energy usage. For those with pro-environmental dispositions, this may trigger conservation behavior. The EEE specifically addresses bounded rationality by removing the cognitive barrier of quantifying what is at stake. This is done by taking every user's individual baseline and applying it to their potential gains at the end of the treatment period. As a result, a comparison can be made between how consumers behave under conditions of certain losses (EEE) and uncertain gains (P4P). While each of the common theories of behaviors (usage feedback and proenvironmental behavior) exist in some form in this experiment it does not explicitly assess the relative influence of each. With a larger sample population and the ability to include different frameworks this could quite easily have been done but is left for future research.

THEORIES OF BEHAVIOR APPLIED TO ENERGY CONSUMPTION

Behavioral economics provides important insights into market failures, including principal-agent conflicts, externalities, information asymmetries, and transaction costs. For instance, consumers can act inconsistently against both their stated and revealed preferences, therefore providing direct challenges to rational choice theory that dominates neo-classical economic theory. In other words, consumer choice is not always consistent with strict utility maximization (Tversky & Kahneman, 1992). Classic welfare analysis assumes that consumers maximize their utility function based on choices constrained only by budgets. Utility functions can be specified based on consumers' revealed preferences but are generally regarded as immutable and inviolable. The problem is that consumers often do not act on their stated preferences, resulting in various types of behaviors, such as procrastination and altruism.

This section focuses on behavioral phenomena across a single, but significant, subset of the economy, the energy sector, and particularly on a small subset of that, residential household behavior. Compared to industrial and commercial energy consumption, household energy consumption has been largely shielded from financial incentives to reduce consumption. Competition within the industrial and commercial sectors has been a more normalizing force when it comes to energy efficiency and consumption. Because market-like arbitrage does not actually exist for many energy and environmental goods and services, behavioral “failures” can affect and be affected by government intervention (Shogren & Taylor, 2008). These interventions can take several forms, including regulation, policy, measurements, and information exchange.

Many researchers believe behavioral anomalies can help explain the differences in observed and socially optimal levels of energy efficiency, sometimes called the “energy efficiency gap” or “energy paradox”, whereby life cycle cost analysis shows short payback periods for required capital investment in most energy efficiency technologies, yet they go unrealized (Gillingham & Palmer, 2013). Two primary forces are contributing to a renewed focus on conservation and behavior within the energy sector, 1) the increased delinking of economic growth from energy consumption, and 2) a renewed concern about environmental externalities associated with energy production, particularly with respect to climate change. In fact, public and private sector concerns about the large quantities of GHGs being dumped into the atmosphere, largely from the transportation and electricity sectors, are focusing attention within the energy sector on environmentally responsible behaviors (ERBs), thus renewing interest in theories of social behavior as they relate to energy consumption.

What is empirically known is that residential households often respond in unpredictable ways to both financial and non-financial incentives. The responses can modulate and even dissipate. Behavioral economics addresses some of these inconsistencies or deviations by formalizing theories of consumer choice. It draws upon cognitive psychology, sociology, and other fields to explain how individuals make decisions. This field statement highlights the most applicable theories within the energy sector with a particular emphasis on DSM and energy efficiency programs and targeted policy tools, such as labeling, choice framing, and usage feedback, some of which can be coined *libertarian paternalism* “nudges” (Allcott & Kessler, 2015; R. H. Thaler & Sunstein, 2009). The policy goal is to assist consumers in maximizing their overall true utility (in contrast to a time-invariant revealed utility) without constraining their choice set. This merging of welfare economics and behavioral economics is (unsurprisingly) referred to as *behavioral welfare economics*.

Currently, there is only a small body of research that examines the impacts of prospect theory applied to the demand-side of the energy sector. The lack of application for loss aversion is particularly acute, prompting one leading energy journal to claim “*We know very little in energy research about how loss aversion impacts energy demand”* (Hahn & Metcalfe, 2016). One of the promising reasons to explore it is because it has a high potential to be integrated into markets, with smart meter technology providing avenues for exploring consumer behavior in ways that were not possible even a few years ago. Unfortunately, the market penetration within residential households of smart meter-enabled information remains remarkably slow. Although utilities receive immediate benefit by remotely collecting usage from smart meters, that information is seldom used to directly incent users to reduce consumption. Traditional rate-based cost-recovery structures, discussed earlier, provide one major barrier by not providing adequate incentives for utilities to curtail consumer demand.

A recent study of intrinsic (financial) and extrinsic (non-financial) incentives to reduce peak demand showed that financial incentives induce larger reductions and are more habit forming (Ito, Ida, & Tanaka, 2018)[15]. Some researchers will occasionally point to these types of studies and claim that utility ‘behavioral programs’ are not as beneficial as financial incentives in reducing consumption. Unfortunately, this label is misleading since the two are not mutually exclusive. This research employs behavioral treatments that examine how consumers respond differently to the *same* financial incentive.

Behavioral science is identified as a way of addressing the six market barriers to energy efficiency identified in the literature: 1) misplaced incentives, 2) lack of access to financing, 3) market structure flaws, 4) inappropriate pricing and regulation, 5) gold plating, and 6) lack of information (Thollander, Palm, & Rohdin, 2010). A subset of these are identified as “behavioral failures”, often a result of information asymmetries (see Table 2).

[15] Because the costs of procuring energy at peak demand is very high for utilities, the overall costs of providing a DR program are much lower. This result should not necessarily be assumed to apply to all energy reduction programs.

Table 2: Market and Behavioral Failures in Energy Efficiency with Potential Policy Responses (Gillingham, Newell, & Palmer, 2009)

Potential Market Failures	Potential Policy Options
Energy market failures	
Environmental externalities	Emissions pricing (tax, cap-and-trade)
Average-cost electricity pricing	Real-time pricing; market pricing
Energy security	Energy taxation; strategic reserves
Capital market failures	
Liquidity constraints	Financing/loan programs
Innovation market failures	
Research and development (R&D) spillovers	R&D tax credits; public funding
Learning-by-doing spillovers	Incentives for early market adoption
Information problems	
Lack of information; asymmetric information	Information programs
Principal–agent problems	Information programs
Learning-by-using	Information programs
Potential Behavioral Failures	
Prospect theory	Education; information; product standards
Bounded rationality	Education; information; product standards
Heuristic decisionmaking	Education; information; product standards

This research directly investigates one type of behavioral response that has the potential to improve individual utility and social outcomes, prospect theory. Specifically, it examines whether loss aversion, can more effectively be employed to reduce the energy efficiency gap as a direct financial incentive that competes against supply-side generation. The possibility appears promising. Many studies show that loss aversion, where personal gains are discounted at a higher rate than losses, is a prevalent behavioral characteristic (DellaVigna, 2009; Tversky & Kahneman, 1981). The U.K. government, for instance, includes loss aversion as one of its seven key principles informing one (of two) behavioral change guides for policy makers (Dawnay & Shah, 2005). This behavioral trait has the potential to redress high discount rates for energy efficiency investments in two ways: a) If potential gains can be framed as potential losses, consumers can overcome cognitive limitations by precisely and overtly stating those gains/losses, and b) it can effectively address the worse aspects of high discount rates, called hyperbolic discounting, whereby individuals exhibit a declining rate of time preference.

This research, thus, has the potential to develop policy approaches that are consistent with libertarian paternalism "nudges" (Allcott & Kessler, 2015; R. H. Thaler & Sunstein, 2009). The policy goal is to assist consumers in maximizing their overall true utility (in contrast to a time-invariant revealed utility) without constraining their choice set.

Behavior and Energy Consumption

Behavioral interventions in energy consumption are generally focused on individual (or micro) outcomes. In contrast, "macro" factors tend to focus on TEDIC[16] factors, which have a more social and techno-industrial component to them. Individual outcomes recognize that reductions in energy consumption can result from very different types of behavior ranging from "one-shot", or efficiency, behaviors, to "repetitive", or curtailment, behaviors (See Table 3) (Martiskainen, 2007). Interestingly, research on energy consumption behaviors has not been able to quantify whether curtailment or efficiency behaviors are more effective in domestic energy saving (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Gardner & Stern, 2002).

[16] TEDIC = Technology (e.g. more energy efficient appliances), Economic growth, Demographic factors, Institutional, and Cultural factors.

Table 3: Types of Energy Consumption Behavior

Behavior Type	Examples
Efficiency	One-shot Insulation Purchase of energy efficient durable good Purchase of fuel efficient vehicle
Curtailment	Repetitive Carpooling Turning off lights Adjusting thermostat

It is important to understand why behavioral interventions deserve further economic study given that energy efficiency behaviors almost invariably reward individuals in a short period of time. A wide variety of individual choices that contradict revealed preferences can be explained by various theories of behavior. This is true even beyond material interests, including pro-social and pro-environmental preferences.

The major departures from neoclassical economics reflected in behavioral economics are generally grouped in four categories: 1) prospect theory, 2) time-varying discount rates, 3) bounded rationality, and 4) pro-social behavior (Pollitt & Shaorshadze, 2011). Although this research touches on all of these groups, prospect theory and loss aversion are most saliently addressed.

Prospect Theory: Loss Aversion and the Endowment Effect

When presented with choices with equivalent expected outcomes, individuals tend to prefer less risk averse options. For example, when presented with an option that could cure a terminal disease affecting 600 persons, 72 percent of respondents favored the program option whereby 200 people were saved over the program option whereby the entire affected population was saved with 1/3 probability (Tversky & Kahneman, 1981). Similarly, people preferred medical options that favored a 90 percent survival rate over the same option that yielded a 10 percent mortality rate (McNeil, Pauker, Sox Jr, & Tversky, 1982). In economic terms this uncertainty-loss aversion bias (ULAB) shows that compensation required for forgoing consumption of a given good typically exceeds the willingness to pay for increased consumption of the same good by several times (Bateman, Munro, Rhodes, Starmer, & Sugden, 1997). This can be expressed mathematically as:

Equation 2: Willingness to Pay vs. Willingness to Accept Model

$$\begin{aligned} V(x) &= \chi^{\alpha} \; if \; \chi \geq 0 \\ &= -\lambda\,(-\chi)^{\alpha} \; if \; \chi < 0 \end{aligned}$$

Where χ is the payoff of the risky choice and V is the perceived utility

Typical estimates for the variables are $\lambda = 2.25$ and $\alpha = 0.88$ (Benartzi & Thaler, 1993a). The endowment effect reflects experiments that show that people are more eager to retain something they actually own than to acquire something new, potentially of higher revealed preference.[17] For example, one experiment showed that a group given a coffee mug would only sell for an average price of $7.12, while another group was only willing to pay $2.87 for the same mug (Kahneman, Knetsch, & Thaler, 1991). This phenomenon helps explain why individuals consistently have higher willingness-to-accept (WTA) thresholds than willingness-to-pay (WTP). This behavioral trait can be challenging in encouraging one-shot, efficiency type activities, such as replacing a highly durable good, because consumers already tend to overvalue their current energy-consuming item.

Across multiple risk experiments losses count roughly twice as much as gains in customers' revealed preferences (De Palma et al., 2008; DellaVigna, 2009).

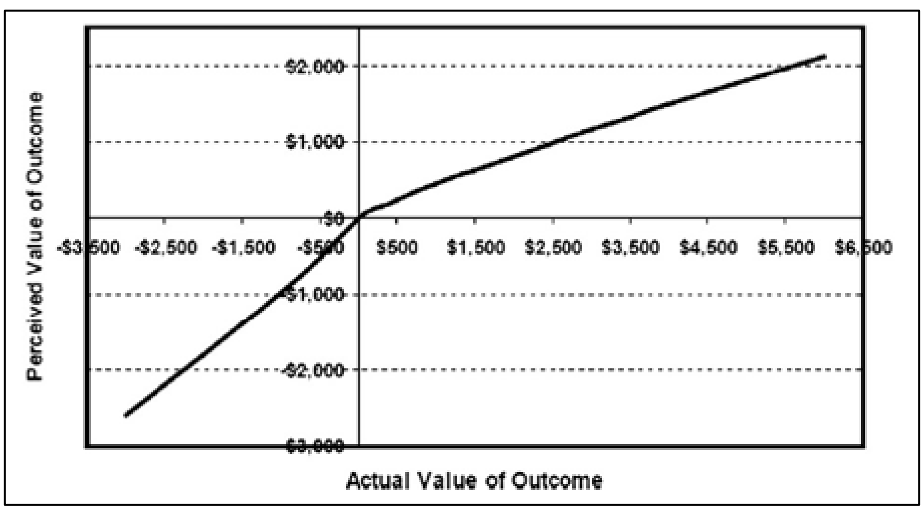


Figure 14: Kahneman and Tversky's Loss Aversion Function (Benartzi & Thaler, 1993b)

[17] For instance, one experiment showed how, when items of the same value (a candy bar and coffee mug) were randomly distributed to participants, preferences to keep the assigned commodity (versus trading for the other) ranged from 10 to 89 percent (Knetsch, 1989).

Both the presence and magnitude of the loss aversion effect varies widely and can depend on multiple factors. For instance, where losses and gains are repetitive and where the amounts in question are not high, actual differences were insignificant, *although emotional affect in losing was still detectable* (Yechiam, 2015). Other factors include:

1. Cultural and ethnic differences (Wang, Rieger, & Hens, 2017)
2. Whether the good is utilitarian (e.g. money) or hedonic (e.g. possession). For instance, some studies have shown there is no detectable loss aversion for money if consumers have committed to spending it. An endowment effect for an object or good can grow as consumers become more attached to it. Even new goods can cause instantaneous attachment effects due to their relative association. (Ariely, Huber, & Wertenbroch, 2005)
3. Level of attention – One study showed that when two tasks are performed simultaneously, one requiring high levels of attention and the other requiring little attention, loss aversion had relatively little effect on the outcome for the high attention task (Yechiam & Hochman, 2013). This may suggest that as consumers are forced or allowed to work through the cognitive barriers of a task, that the inherent losses are seen as proportional or commensurate with the gains.
4. Emotions can affect consumers' WTA. One study showed that sadness is more likely to cause a consumer to facilitate trading. (Lerner, Small, & Loewenstein, 2004)

Another reason loss aversion may be important in explaining the energy paradox is because predicting *exact* future energy savings from energy efficient products is difficult and will certainly show considerable variance. For instance, 1) products will be used in different ways from which they were tested/rated, 2) future energy prices will change, 3) products will be used at different rates, and 4) product lifetimes will vary. So, although the net average savings may be considerably net positive, the bias toward loss aversion may not move some consumers toward purchasing even though they are likely to benefit[18]. Loss aversion has been modeled to explain revealed discount rates in the context of vehicles and fuel-efficiency performance. (Greene, 2011; Hassett & Metcalf, 1993).[19] However, empirical evidence of loss aversion as a behavioral failure in consumers' energy choices continues to be sparse, this despite the fact that many governments and researchers view it with great potential.

Time-inconsistent Preferences and Hyperbolic Discounting

"Time preferences" have been interpreted as "an amalgamation of various intertemporal motives" (Frederick, Loewenstein, & O'Donoghue, 2002, p. 355). In other words, it is shorthand for the effects of multiple influences that affect behavior and, therefore, cannot be used as uniquely deterministic model. Individual discount rates are, in fact, not constant over time and vary across types of intertemporal choices: 1) gains are

[18] Of course, given the high number of uncertainties, one or more of which may trigger loss aversion behaviors, may also contribute to other types of behaviors, such as simplified heuristics (e.g. bounded rationality).

[19] There is little research to show how "learning by using" new energy efficient technology may contribute to reduced consumption. This may be increasingly relevant in the future for two reasons: 1) technology diffusion may be a function of how well early adopters can optimize new technology, and 2) there are an increasing array of technologies that can potentially interact to create synergies (e.g. wireless technology and smart appliances, smartphone apps and smart meters).

discounted more than losses, 2) small amounts more than large amounts, and 3) decisions with multiple outcomes differ from those considered singly (Frederick et al., 2002, p. 360).

Hausman was a pioneer who first demonstrated that consumers heavily discounted future energy savings in the purchase of room air conditioners (~ 20 percent) (Hausman, 1979). Other studies included the market for used motor vehicles (~ 24 percent) (Allcott & Wozny, 2013), and durable goods (20 – 50 percent) (Train, 1985). Table 4 shows a range of discount rates from multiple studies for the purchase of various durable goods (Team).

Table 4: Discount Rates for Various Energy-Related Durables and Investments

Category	Discount rate (%)
Thermal insulation	10–32
Space heating	2–36
Air conditioning	3.2–29
Refrigerators	39–300
Lighting	7–17
Automobiles	2–45

Sources: Train (1985); DEFRA (2010).

Experimental economics is replete with examples of individuals exhibiting a declining rate of time preference. In other words, the implicit individual discount rate over a longer period is lower than for shorter periods. Sometimes referred to as hyperbolic discounting, one popular study revealed that individuals, when given $15, are indifferent to parting with that if compensated with $20 a month later (a 345 percent discount rate), $50 a year later (a 120 percent discount rate), or $100 ten-years later (a 19 percent discount rate) (R. Thaler, 1981). Similarly, a consumer may prefer $100 today to $105 tomorrow yet prefer $105 a year and one day from today to $100 a year from today[20]. Although this clearly violates utility theory axioms it reflects how individuals manage risk (Gong, Smith, & Zou, 2007). These tendencies have been difficult to quantify with respect to energy efficiency investments and energy use (Prindle & others, 2007).

Although this study does not specifically address time-inconsistent preferences, which dominates "efficiency" type behavior (see Table 3), it can certainly provide a basis for how consumers may behave when faced with information that quantifies their usage.

Information Asymmetries

Usage Feedback and Social Comparison

Feedback is the process of giving individuals information about their behavior. It has been used in many policy areas, including public health, education, and organizational behavior. Norm activation theory emphasizes the importance of *awareness* of behavioral actions in influencing outcomes. Awareness helps reinforce a person's behavioral intentions by reducing the likelihood that he/she simply is not paying attention. For electricity or natural gas consumption, this is particularly relevant since most consumers are only aware of their usage habits once a month when they get their

[20] A somewhat special case of time-inconsistency reflects individual preferences toward avoiding near term costs regardless of the longer-term savings. Although closely related to hyperbolic discounting, this phenomenon refers to situations where, as the future nears, regardless of the consumer's specific long-term discount rate, discounting becomes steep. Also referred to as "self-control problems", this nonstandard preference has been used to explain why individuals fail to stop smoking or eat healthier despite their stated preferences.

energy bill. Contrast this with driving habits, which are much more responsive to gasoline prices and a feedback routine (fuel gauge) with much higher frequency.

Feedback can take on a variety of forms, sometimes differentiated by indirect and direct methods. Indirect methods include enhanced billing and estimated feedback, using tools such as online energy audits. Direct or real-time feedback generally refers to using devices such as in-home displays (IHDs). The effect of usage feedback may differ somewhat depending on an individual's utility function, which reflect myriad tradeoffs and marginal costs of substitution, but feedback is unlikely to change behavior if their existing behavior is not compatible with their values and beliefs (Martiskainen, 2007).

Direct energy feedback studies generally confirm that providing more frequent usage feedback will reduce homeowner electricity consumption to some degree, although the levels vary widely, from 3-20 percent (Abrahamse et al., 2005; Darby, 2006; Seligman & Darley, 1977). This result matches well with international studies that show a short-term energy savings from 5-15 percent (Martiskainen, 2007). A meta-analysis of 42 studies shows a mean effect size of 7.1 percent (Karlin, Zinger, & Ford, 2015).

Few studies, however, have examined how direct feedback works in concert with other incentives. One study indicates that the direct feedback provided by IHDs encourages consumers to make more efficient use of energy, ranging from, on average, about 7 percent when prepayment of electricity is not involved to about 14 percent when consumers use both an IHD and are on an electricity prepayment system (Faruqui, Sergici, & Sharif, 2010).

Even fewer studies have incorporated IHDs with other forms of information that might further alter behavior. This study contributes to the literature by combining financial incentives with two frameworks that employ loss aversion and risk management. One recent study examined how internal value and tailored action prompts delivered through IHD-enabled smart tablet changed behavior. This approach is termed intelligent smart metering (ISM) (Mogles et al., 2017).

Some caution must be taken in estimating savings from IHDs, however. This is particularly the case in estimating mid to long-term reductions where significant reductions evaporated in only 15 months (Dam, Bakker, & Hal, 2010). Others argue there is simply not enough research to assess the overall efficacy of IHDs (Buchanan, Russo, & Anderson, 2015). Also, IHDs are typically deployed as stand-alone devices. This may actually inhibit how consumers interact as more information is being consolidated onto shared platforms, such as smart device applications. IHDs that are not dynamic or that repeat the same information can suffer from the "fallback effect", where old information fades into the background of user behavior (Wilhite & Ling, 1995).

Usage feedback can help users understand social norms and how their habits compare to others in comparable social and regional settings. This type of behavioral intervention has yielded the highest interest among energy providers to date. Multiple utility companies have used home energy reports (HERs) to allow households to compare energy usage with comparable households. Typically, HERs give descriptive norms outlining how household energy usage compares to local averages as well as other diagnostic comparisons. Customer behavior change is based on both theories of social norm conformance (aka “norm to conform”), as well as increased information and user awareness (user feedback). Peer comparison has shown dramatic changes in behavior in other conservation arenas, such as encouraging towel reuse at hotels (Goldstein, Cialdini, & Griskevicius, 2008), reducing residential water usage (Ferraro & Price, 2011), and installing energy-efficient light bulbs (Ferraro & Price, 2011). It is important to distinguish types of informational, either normative or descriptive, with disclosure requirements, such as restaurant hygiene grades. The efficacy of disclosure, in fact, can depend greatly on the framing, content, and form of delivery (Ayres, Raseman, & Shih, 2013).

A review of twenty social comparison studies that met stringent causality standards showed reductions between 1.2% and 30% (Andor & Fels, 2017). In two of the largest studies, one that included over 600,000 households, and another that included 170,000 residential customers covering two utility service areas (one for electricity and the other for natural gas), reductions in energy consumption ranged from 1.4% to 3.3% (mean = 2%) (in the former), and 1.2% and 2.1% over a 7 and 12-month time period with no observed boomerang effect whereby individuals feel compelled to use more energy upon learning that they are lower-than-average (Clee & Wicklund, 1980). In fact, one study found this to be true for a relatively small number of low-use users (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007). One way of overcoming this is by the use of injunctive norms, such as using smiley faces or frowns, to express social values rather than actual behavior. Lastly, HERs have generally resulted in sustained decreased consumption. Additionally, social norms tend to have a stronger effect on heavy energy consumers (Allcott, 2011; Ayres et al., 2013).

The management of these peer comparison programs not only yields cost savings to customers but also provides a cost-effective way for utility companies to meet energy requirements. For instance, studies show that it costs about 0.025 $/kWh to reduce demand versus a range of higher-cost supply options. For a given service area, it can reduce carbon emissions by 0.5 percent and has the potential to save $2.2 billion per year in the U.S. (Allcott & Mullainathan, 2010). Furthermore, and very important to policymakers, HER programs have shown to have persistent effects beyond program cessation. One important study showed that consumers who participated in HER programs invested substantially in capital efficiency investments, not just curtailment behavior. Approximately 35 to 55 percent of energy consumption reductions can be attributed to efficiency upgrades, which are persistent (Brandon et al., 2017).

Most studies of HERs base their findings and potential benefits strictly on reduced consumption and reduced energy spending. However, a few very recent studies have evaluated consumers' WTP for HERs and found that a small, but significant, number of consumers actually would pay to *stop* having HERs delivered, meaning that they have negative utility in some instances. This presents an interesting additional consideration for energy policy, for blanket delivery of HERs does exert some negative societal outcomes (Allcott & Kessler, 2015).

Public Commitment, Cooperation and Goal Setting

Game theory in public goods games have a long history in economics and strategic studies. Variations of these, including cooperation, reciprocity, and punishment games are very common both in laboratory and field experiments but have very little empirical research within the demand side of the energy sector. This is slightly unusual considering the scope and nature of the energy sector, as well as the potential gains that these behavioral insights could yield.

Cooperation is the willingness to incur personal costs for the common good. It reflects variations of the Prisoner's Dilemma game where total social benefits can only be optimized through trust, while personal gain is placed at risk. Self-interest can undermine cooperation and lead to free-riding. Rational, self-interested individuals are always predicted to defect yet decades of experiments show cooperation rates range from 40 to 60 percent (Bicchieri, 2006, p. 140). Another critical factor to individuals is reputation, thus requiring levels of *observability*. There is evidence that publicizing the names of donors increases the frequency of blood donations (Lacetera & Macis, 2010) and levels of charity giving (Karlan & McConnell, 2014).

One of the few large-scale, field-experiment cooperation games in the energy sector, which evaluated incentives to allow the utility company to reduce peak demand, found that 1) observable, voluntary relinquishment of central A/C control during high demand, framed as a public good, was more effective than a $25 incentive[21]. Also, volunteers were three times more likely to sign up if their participation was publicly

[21] The study found that it would take a $174 incentive to offset the perceived gains of being in the observable treatment group.

shared relative to the anonymous treatment group, 2) this effect was more significant in densely populated areas, such as apartment buildings, where neighbor interaction is more frequent and reputation concerns matter more, as well as in residences where the tenants owned the property versus rented (adding to other principal-agent challenges previously discussed). To verify that observability was a critical element of cooperating in the public good, another treatment group responded to a similar solicitation stripped of language referring to demand response as a public good, and there was no statistically significant differences in those choosing the publicly shared option and the anonymous option (Yoeli, Hoffman, Rand, & Nowak, 2013).

Bounded Rationality

Bounded rationality is another general classification of behavioral economics that describes why rational choice is constrained by limitations on time and imperfect (or non-existent) information, often coupled to influence a consumer's cognitive abilities. Neuroeconomics, a nascent field of research, is dedicated to understanding the mental processes involved in personal decision-making. Also called "Nonstandard Decisionmaking" (DellaVigna, 2009), different decision-making heuristics or mental shortcuts can be used to explain such behaviors as procrastination and overweighting *observable* factors, such as the purchase price of an energy efficient durable good. This is especially true if the energy costs are small compared to the purchase price (Jaffe & Stavins, 1994a).

Mental accounting is a known behavioral framework which predicts that people will spend money coming from different sources in different ways. That is to say that depending on the actual good or service being consumed, consumers reveal different preferences based on a relative reference point. For instance, the difference between $10 and $20 seems bigger than the difference between $500 and $510, and in percentage terms the difference is significant (100 percent versus 2 percent). Although the absolute savings (or loss) is equivalent, consumers may choose to incur some cost (e.g. take time to switch plans or travel across town) based on the relative change to an expected cost (R. Thaler, 1985). This framework is yet another departure from classical economic theory that suggests money is fungible and is indifferent to income sources (R. H. Thaler & Sunstein, 2009). This mental model could have profound effects for energy efficiency, for if consumers have built a ceiling threshold for energy consumption, and that ceiling is not exceeded, the ability to pursue greater savings (no matter the cost) may become very difficult. Consequently, it could help explain the relatively high discount rates for energy efficiency purchases. The lack of empirical information within the energy consumption sector to quantify this effect limits policy development. However, given that energy consumption is so disaggregated from a transaction perspective (e.g. gasoline for vehicles, natural gas for heating, electricity), it is intriguing to see how mental accounting may change behaviors if/when it becomes more aggregated; for instance, if more households use electricity for transportation.

Framing and Default Options/Status Quo Bias

Default options for residential household energy consumers have gotten attention from researchers on the supply side. With the restructuring of the electricity industry in the 1990's many states deregulated either wholesale or retail markets. The motivation was that consumers, not utility companies, could best decide the mix of generation sources that were valued and, thus, make for a more competitive marketplace. In turn, that would lead to lower electricity prices. The results have been mixed. One of the challenges for regulators has been to find effective ways for consumers to make informed choices about their energy provider. This can be confusing since consumers are not necessarily knowledgeable about these options and are used to working with a single provider, which is their local energy distribution company (LDC). They are required to provide a default option.

In Pennsylvania, which has unregulated retail electricity markets, less than a third of residential customer have opted out of the default electricity provider compared to 43.7 percent and 79.1 percent of commercial and industrial customers (PA Power Switch, 2019). The default residential rate is set by the LDC, who only provides transmission and distribution service to the residential service area. The default rate is often neither the cheapest nor the most environmentally beneficial. The LDC, who monitors consumer usage, is not necessarily incentivized to ensure each customer understands and can navigate their provider choices.

The other extreme of the choice spectrum can be equally costly for consumers. When presented with too many choices, customers often decide not to decide. This is famously reflected in the "jam study", whereby customers who were exposed to six types of jams were more likely to make a purchase than those exposed to 24 types (Iyengar & Lepper, 2000). In one of Pennsylvania's largest service areas, customers must navigate through 165 energy providers, with a variety of fixed and variable rate and term length offerings.

How options are presented to consumers has been shown to have a substantial effect on their behavior. Consequently, labeling and positive messaging have observable effects. This appears to be more salient when consumers have to make choices from a large choice set with multiple attributes, such as a pension plan, health insurance, or a new vehicle. The high revealed discount rates of Table 4 could possibly be explained by inattentive behavior or imperfect information (or both). This assertion could explain other empirical studies that show that consumers are inattentive to "ancillary product costs", such as sales taxes (Chetty, Looney, & Kroft, 2009) and shipping and handling charges (Brown, Hossain, & Morgan, 2010), or out-of-pocket insurance costs (Abaluck & Gruber, 2011). In the context of durable good purchases or household efficiency upgrades, limited attention may be due to the relevance (or irrelevance) of energy efficiency in a decision-maker's subjective experience (perhaps due to the relatively low monetary expenses for electricity), or because the topic is not generally addressed in the media. This suggests an "availability bias" against infrequent (one-shot) type behaviors (Schubert & Stadelmann, 2015).

Product labeling represents another effective tool by which policymakers can not only reduce information asymmetries, but also frame consumer choices. Since 1980, the Federal Trade Commission (FTC) has required appliance manufacturers to provide "information" about the operating costs of their products. The Energy Policy Act of 2005 (EPAct 2005) required the FTC to look at more effective designs for the EnergyGuide label. One major study showed that simple information on the economic value of energy savings was the most important element guiding consumer decisions to invest in energy efficient water heaters (Newell & Siikamäki, 2013). Still, certifications (e.g. Energy Star) (Ward, Clark, Jensen, Yen, & Russell, 2011)[22] or grades (e.g. EU-style label) are also effective, as was information on physical energy use and carbon emissions. The cumulative effects of each label treatment were also additive, although at differing levels depending on the combination. Two other important findings showed that individuals with higher revealed discount rates were more responsive to the labeling features than those with lower discount rates[23], and 2) those with higher discount rates were *less* likely to take advantage of federal EE tax credit claims, showing an *increase* in potential free-ridership for some durables. As an important policy finding, the study did show that there were labeling structures that caused consumers to *overvalue* energy savings relative to their revealed individual discount rates (median rate = 19 percent). Although these labels may help overcome the energy paradox, it does reveal a cautionary warning regarding "liberal paternalism"; that is, should labels that require users to overvalue future costs be encouraged despite consumer revealed discount preferences? In other words, although it may be to the individual's economic interest to encourage energy efficiency, nudging should ideally encourage individuals to *experience* their *revealed* utility.

[22] Consumers, on average, are WTP an extra $249-$349 for a refrigerator with the Energy Star label. Associated studies found that household characteristics, such as renter status, ethnicity, income, and living in states with lower ACEEE scores decrease the propensity to purchase Energy Star appliances (Murray & Mills, 2011).

[23] For example, going from a 10 to 20 percent individual discount rate (100% increase) will cause a 10 percent reduction in WTP for $10 in annual energy savings.

Other studies have suggested that even when energy costs are fully presented as a function of total operating costs, they do not always change consumer purchasing decisions. One study, for instance, found no effect of fuel economy information affecting vehicle purchasing decisions (Allcott & Knittel, 2017). Because certain durables, like vehicles, have a good deal of feature differentiation, perhaps researchers are undervaluing consumer utility in unmeasured variables.

Of course, loss aversion can have profound effects on framing. These types of framing techniques suggest information such as “You are currently losing $10/month by not using fluorescent lightbulbs” may be more effective than suggesting they could save the equivalent amount. However, this type of framing may be less effective when directed away from personal consumption and toward social contexts (Frederiks, Stenner, & Hobman, 2015). In this sense, the Energy Efficiency Escrow (EEE), described below, is itself a type of framing mechanism that constantly reminds the user of what exactly is being lost when they choose to consume. Variations of the EEE could include rates at which the escrow is diminishing, much like the fuel efficiency gauges on newer vehicles.

Although opt-out energy efficiency, time-variant pricing and home energy report (HER) programs are effective, the marginal savings per additional customer for utility companies is less than for opt-in programs. That is because those who opt-in are generally more informed and motivated to conserve energy. For time-variant pricing programs, average adoption rates are around 80 percent when customers are given the choice to opt-out compared with 15 percent for opting in; the latter option still tends to be the norm for those types of programs.

Pro-environmental Behavior

The values, beliefs, and norms (VBN) theory suggests that proenvironmental behaviors stem from acceptance of particular personal values, from beliefs that things important to those values are under threat, and from beliefs that actions initiated by the individual can help alleviate the threat and restore the values (P. C. Stern, Dietz, Abel, Guagnano, & Kalof, 1999). It is an integration of two theories, the theory of planned behavior (TPB) promoted by Ajzen, that beliefs antecede behavioral intentions, which in turn antecede actual behavior (Ajzen, 1991), and Schwartz's moral norm-activation theory (Schwartz, 1977), referring to a process in which people construct self-expectations regarding prosocial behavior. These behavioral self-expectations are termed 'personal norms' and are experienced as feelings of moral obligation. Central in the process of norm activation are six factors that are incorporated within (and added upon) the VBN model: 1) Awareness of consequences, 2) awareness of need, 3) situational responsibility, 4) efficacy, 5) ability, and 6) denial of responsibility.

According to TPB, the main determining factors of behavioral intention are attitudes, which are influenced by knowledge and experience, subjective norms that the consumer believes is acceptable by society, and the perceived impact of the behavior. VBN adds to this causal chain by demonstrating that environmental beliefs are anteceded by personal *values* (e.g., altruistic, egoistic). Stern emphasizes that environmentally significant behaviors are affected based on the interplay of a wide range of contextual and attitudinal causal variables. In particular, he finds it useful in distinguishing between private sphere environmentalism (e.g. consumer purchasing choices) and public sphere environmentalism (e.g. activism, petitioning), emphasizing that a unifying *general* theory of environmentalism is quite likely unattainable. Consequently, VBN theory is designed to explain nonactivist environmentalism (P. C. Stern, 2000).

VBN theory focuses on a narrow set of attitudinal factors that describe a consumer's general disposition to act with proenvironmental intent. This is distinct from other attitudinal factors, including behavior-specific predispositions (related to norm activation theory) and behavior-specific beliefs. In this respect VBN applies norm activation theory in a general sense. As such, VBN theory is not a unifying theory of consumer behavior and the interactions between attitudinal and contextual variables are complex and evolving (P. C. Stern, 2000). However, many studies indicate that *personal values* are most significantly associated with activation of proenvironmental personal norms (Karp, 1996; P. C. Stern, Kalof, Dietz, & Guagnano, 1995).

Some contend that environmentalist intent is not even among the more critical factors in predicting environmental-related outcomes. Habits, income, community infrastructure (e.g. access to public transportation) constrain the choices among consumers who value the environment equally. One study showed substantial differentiation among pro-environmental behavior patterns with respect to individuals who have positive environmental dispositions, supporting the notion that behaviors are situational-specific *or* that the mechanism by which personal norms are activated are still not clearly understood. (Cleveland, Kalamas, & Laroche, 2005). Because the interplay of all contextual and attitudinal factors within the VBN model are complex, this research can likely not be generalized. For instance one study involving curbside recycling showed that attitudinal variables are less important when certain contextual forces are strongly positive (compelling) or negative (prohibiting) with respect to the behavior in question (Guagnano, Stern, & Dietz, 1995). Other studies have shown that positive environmental behavior is not strongly favored by contextual variables that are more difficult, time-consuming, or expensive (Black, Stern, & Elworth, 1985). Few studies have been conducted to compare attitudinal factors with contextual factors.

Another body of theory associates positive environmental behavior with postmaterialist values of quality of life and self-expression (Inglehart, 1990). One 27-country sample provided strong postmaterialistic value correlation with environmental concern, perceived threat, perceived behavioral control and willingness to sacrifice, affecting a variety of pro-environmental behaviors (Oreg & Katz-Gerro, 2006). Although many of the triggering mechanisms that support the VBN model are present in postmaterialist theory, the more constrained level of analysis covered in this research (U.S. energy consumers) is unlikely to differentiate dramatically due to postmaterialist values.

Research Questions

The following include the primary research questions for the experiment. They attempt to integrate emerging DSM policy trends with theories of behavior that have not been applied to the energy sector.

Financial Incentives for Energy Reduction

Research Question: Does the employment of a rate-based financial incentive reduce personal energy consumption?

Hypothesis: A financial incentive will reduce personal energy consumption across multiple frameworks (EEE and P4P).

Research Question: Do individuals with a higher potential reward for reducing energy, reflected in a higher baseline usage level, perform better relative than others?

Hypothesis: Individuals with a higher potential reward for conserving energy will reflect higher levels of energy reductions than those with lower potential rewards.

Performance of EEE versus P4P

Research Question: Does the employment of an energy efficiency escrow (EEE) reduce consumption relative to the same financial incentive presented as a potential gain, modeled by a P4P program?

Hypothesis: The EEE incentive will result in lower energy consumption relative to the same financial incentive framed as a P4P program.

Research Question: Do levels of consumption reduction increase over time for the EEE group?

Hypothesis: The EEE group will show greater levels of consumption reduction as the incentive period approaches its conclusion.

RESEARCH DESIGN

This research makes several contributions to the literature on behavioral theories applied to energy consumption. First and most important, it examines whether two separate frameworks that employ the same financial incentive to conserve energy yield substantially different results. One framework (EEE) is structured to stimulate loss aversion explicitly, while the other (P4P) invokes potential gains implicitly, under conditions that require the consumer to use cognition to achieve desired outcomes.

Second, this research examines to what degree, and to which types of consumers, do financial incentives, in general, reduce the monitored consumption of individuals. It does so in a way that employs real-time usage feedback, the ability to remotely control loads, and to monitor personal usage history. A small number of utilities are just beginning to provide rate-based incentives to reduce residential household consumption, but few reliable studies exist to bound how consumers respond.

Third, it examines how individuals respond to financial incentives based on a series of sociodemographic and energy usage factors. These include age, gender, race, financial assistance, and study co-participation. Additionally, it assesses how/whether personal consumption is related to interactions with the usage feedback device, how well they understand the incentive being presented, and how the magnitude of the potential reward affects performance outcome.

Design Outline

The primary data examined in this dissertation is drawn from a field experiment conducted over two-semesters (~ 9 months) at Dickinson College. This method was chosen in order to increase external validity by measuring how energy consumers respond in a natural environment over a timeframe significantly longer than experienced within a laboratory. Several months of discussions with multiple utility companies failed to result in a residential household pilot study. Thus, resource constraints made a wider, more comprehensive, study impossible. However, given that no empirical evidence exists in the literature about how loss aversion or residential P4P programs would work in the context of energy efficiency incentives, it was determined that this research had policy implications that could inform future household studies.

The experiment was designed to determine how/if individuals (students) would respond to the same financial incentive to reduce energy consumption ($1 for every kWh used below a baseline) provided in two separate frameworks. The unit of analysis are individual students. Institutional Review Board (IRB) approval was granted in September 2018 by Dickinson College.

Two groups were formed and studied in a randomized control trial (RCT), with the control group replicating a traditional pay-for-performance (P4P) program. Both groups received a treatment of a financial incentive. Since P4P provides a framework that currently exists, it is termed the control group for simplicity sake. However, it is important to note that there is no historic performance comparison for the control group given that this research implements P4P quite differently than do current residential household programs, including the level of usage feedback.

The treatment group was provided the same financial incentive, but framed as a potential loss. The mechanism, an energy efficiency escrow (EEE), provided consumers with their maximum possible incentive on day one of the treatment period. That is to say, their EEE showed a balance that reflected what their individual reward incentive would be at the end of the treatment period *if they consumed no energy at all*. The EEE balance would then decrease for each unit of energy (kWh) they used during the treatment period.

The baseline collection period of four weeks (28 days) (Feb 9 - Mar 9) was used to establish each individual's average use. A pause in the experiment occurred during the spring break. The treatment period, whereby the financial incentive was in place, lasted seven weeks (49 days) (Mar 18 – May 6). Each student was offered $25 to participate. Additionally, any student who either had a balance on their EEE at the end of the treatment period (EEE group) or who used less than their individual average baseline (P4P group) was compensated $1 per kWh saved (Figure 15). All payments were in cash.

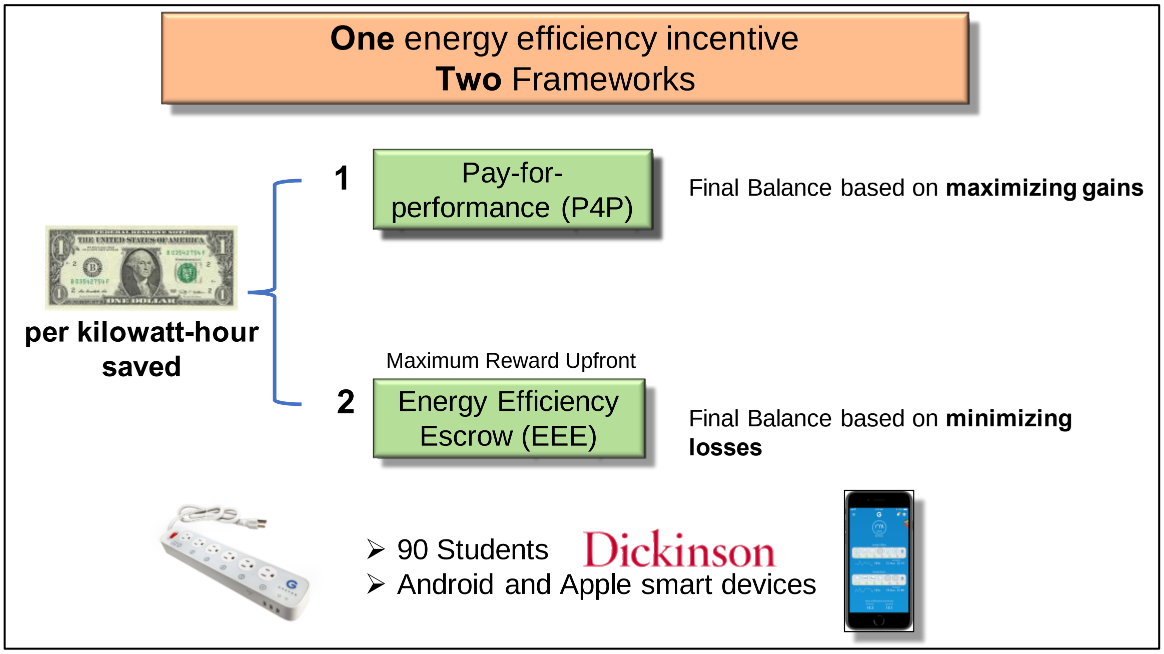


Figure 15: Field Experiment Overview

All students who participated were by definition "opting in" to the study. All students were briefed and reminded that they had the option to opt-out at any time and would retain their $25 participation fee. No students chose to do so. This is noteworthy as some behavioral efficiency programs have triggered some participants to opt-out. This design did not employ any communications, such as injunctive norms, to indicate to students how they were performing relative to other students, nor did it share energy usage of other participants. Only personal usage information was shared with each participant via the GOEFER app.

Design Features

Dickinson College was chosen for the field experiment. All students living in on-campus housing who were at least 18 years old were sent emails (see

Appendix A) promulgating from the Director of Residence Life and Housing at Dickinson College. This took place in early October 2018. A smaller set of students were recruited in early Spring 2019 from invited requests to discuss the project in several classroom lectures[24] All participants were required to sign consent forms, take pre and post experiment surveys, and agree to download the GOEFER app that was used to assist them in monitoring their energy usage and incentives. The Fall 2018 semester was primarily used to ensure experiment hardware and network connectivity was stable.

All students resided in one of eighteen on-campus residence halls. They ranged in size from single to multi-student configurations with the vast majority residing in either single or double occupancy rooms (68 out of 90). Room sizes ranged from 200 sq-ft (single rooms) to around 1000 sq.ft. (4-room apts.). Because space heating/cooling was neither an energy load directly measured nor allowed to be controlled directly by students, room-size differentials were not expected to be a factor. Figure 16 provides a summary of the design layout. Although an inventory of plug loads was not taken for each individual, an informal review of typical loads included, lamps, computers with monitors, mini-refrigerators, stereos, video game consoles, televisions, coffee makers, small microwave ovens, and small fans.

[24] Of the final sample population of 90 students, 71 were recruited via email and 19 recruited via classroom invites early in the Spring 2019 semester. See Appendix A for the text of the recruitment email.

- Framed field experiment – Similar to a Randomized Control Trial (RCT)
- 90 Students
- Unit of analysis = individual students
- 1 control (P4P) and 1 treatment group (EEE)
- 1-3 powerstrips per student
  - Represents all plug-level loads (~40 percent of total load)
- Energy levels collected multiple times per second → aggregated to 15 min. intervals.

Figure 16: Summary of Research Design Parameters

Several orientation sessions were provided throughout the Fall 2018 and early Spring 2019 semesters to issue power strips, to demonstrate their use as well as the accompanying app, and to review the requirements for participation. Each student was allocated as many power strips as they needed to account for their entire plug level demand and to minimize any unnecessary disruptions that may result from plug loads being in disparate locations within the residence. As a result, each student received anywhere from one to three powerstrips.

The guidelines for usage stated that:

a) All individual plug level loads must be connected to an assigned GOEFER power strip. For participants in single rooms, this meant all plug level loads were connected to a GOEFER power strip.

b) All users would download the GOEFER app on an Apple or Android device of their choice.

c) For participants in rooms where all residents are participating in the study, any shared plug loads (e.g. refrigerator) must be assigned to one of the participant's power strips and remain there for the duration of the study.

d) For participants in rooms where not all of the residents are participating in the study, any shared plug loads can either be in an unmonitored outlet, or assigned to a GOEFER power strip. It must remain in that configuration for the duration of the study.

Another consideration in the study was how to account for the effect of providing each student with a smart device app that makes each of them more aware of their own energy use (dependent on how often they check their app). As mentioned earlier, in-home devices (IHDs) tend to reduce consumption without any additional incentive. Because the GOEFER app effectively serves as an IHD it is expected that some reduction took place as students became more familiar with the study hardware and IT equipment.

Students downloaded the GOEFER app asynchronously over the fall and early spring semesters as new students received orientation. As such, it was not feasible to monitor energy usage for each student in order to directly determine usage feedback effects. However, it was assumed that the usage feedback effects, as enabled by the GOEFER app, had already been reflected in each student's energy consumption by the time the baseline collection period began. Additionally, although the GOEFER archiving system logs when each user interacts with the app, no attempt was made to precisely calculate how the GOEFER app interaction reduced consumption for each individual student during the baseline or treatment periods.

The GOEFER energy management company worked directly with the researchers to develop app features, maintain a web-based, real-time dashboard, provide technical assistance, and archive the energy use of all participants in the study. They also provided technical support to students who needed assistance in setting up accounts, pairing the powerstrips with the wifi network, and updating to new versions of the app. Although there were features on the app that were common to all GOEFER users, the version of the app used in the treatment period was customized to meet the requirements of the experiment.

Determining Group and Sample Size

The use of a power analysis to determine the ideal number of groups and sample size was limited by two constraints, 1) there is no public data that indicates the mean and standard deviation of typical college students' energy use, including plug-level loads, and 2) there were financial constraints as to the total number of power strips that could be procured and issued. For these reasons it was decided to not maintain a third control group that received no financial incentive. Having fewer than 45 students in a group would likely dilute the significance of any findings. Still, given the high sample rate and long duration of the treatment, the data set is very robust and an accurate and complete reflection of plug-level usage for both groups.

The hypotheses of the research remained undisclosed to the participants throughout the experiment. The purpose was kept generic and simply revealed as "a research project…..on energy usage". Informal post experiment interviews and discussion confirmed that students were not aware of the purpose of the experiment prior to volunteering.

Constraints and Limitations

While a full collection of electricity usage for each student would be optimal, practical considerations limited doing so. Individual rooms are not metered. Also, it would be difficult to account for individual usage where much of the energy use is shared amongst roommates. For instance, lighting and space heating/cooling are both energy loads that cannot be easily allocated to individual use in shared rooms. Power strips offered the best opportunity to isolate energy use with individual behaviors while still accounting for a significant portion of the total energy demand.

Experiment rule compliance could not be fully enforced except by periodically reinforcing the requirements of the study rules. Several times during the study an email would be sent to students reminding them of the requirements. It should be noted that despite this constraint, since the financial incentive was the same in each group, the benefits to cheating were equally available to those in all groups. Thus, any cheating, if it occurred, would not be biased toward either the control or treatment group.

Experiment Preparation

Hardware Selection and Network Connectivity

The GOEFER energy management company was contracted to provide hardware and IT services for the study. This included the procurement of 157 power strips (Figure 17). See

Appendix B for spec sheet.

Figure 17: Image of GOEFER power strip

Each strip consisted of six outlets and three USB ports. Although power was collected and archived at the individual outlet level, all power levels were aggregated, including those using multiple power strips.

Each student was required to download the GOEFER app on an Apple or Android device of their choosing. Figure 18 shows the home screen of the app. Some important features of the app include: 1) the ability to turn individual outlets on/off, 2) real-time power use by outlet, 2) an energy history tab that shows daily/weekly/monthly energy use. These features were common on the initial version of the GOEFER app.

Figure 18: Home screen of GOEFER app

A web-based dashboard was available to the primary researcher which gave real-time status on power strip connectivity and selectable energy history usage information. This allowed the researcher to filter by calendar range (date/time), student, and resolution[25]. A graph provided the power history for the selected range. Figure 19 shows the dashboard display (upper panels) from a random query taken from Feb. 4 – Feb 7. The “Watts over Time” panel shows the aggregate power consumption of all participants during that period. Below that panel, the “Watts Over Time by Student” panel shows the individual consumption use of all participants. Individual user consumption could be filtered to show higher resolution. The dashboard also shows that, at the time of the query, all 157 power strips were connected to the network and all 90 students were reporting data.

[25] Individual power strip collection intervals included 1 minute, 5 minute, 15 minute, and 1 hour intervals.

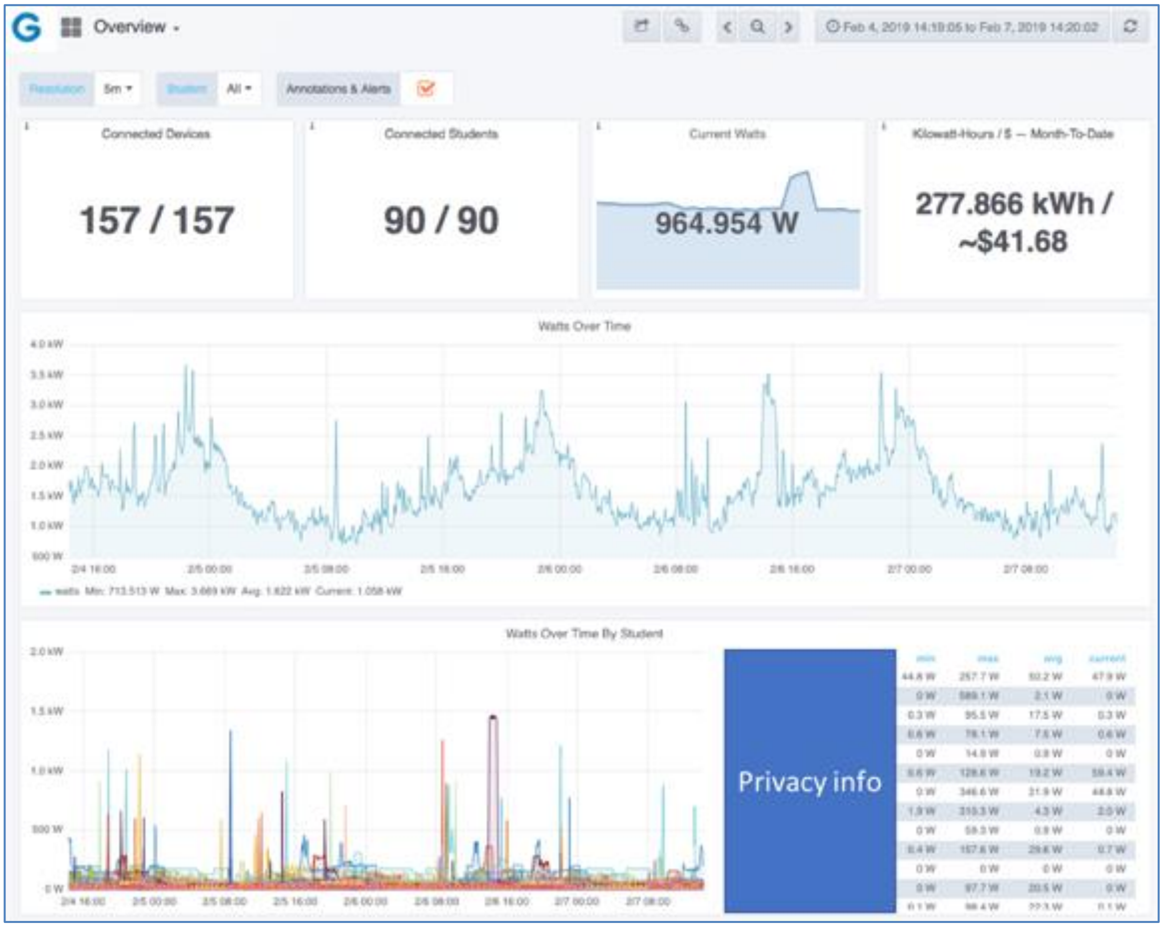


Figure 19: GOEFER Dashboard (upper panels)

The dashboard display (lower panels), "Student Info" panel, provided more granular information by student. The "Num. Issued" column showed the number of power strips assigned to each student in a stoplight chart fashion. Additionally, for the calendar range selected, each student's energy consumption would display in the "kWh" column. The researcher could scroll through this panel to get a quick update on each participant's energy consumption history and connectivity status.

Table 5: GOEFER Dashboard (lower panels)

Student Info			
Email ▲	kWh	Num. Connected	Num. Issued
Privacy Info	3.613 kWh	100%	2
	0.153 kWh	100%	1
	1.260 kWh	100%	2
	0.537 kWh	100%	2
	0.064 kWh	100%	1
	1.380 kWh	100%	2
	1.573 kWh	100%	1
	0.306 kWh	100%	2
	0.068 kWh	100%	1
	4.273 kWh	100%	2
	0 kWh	100%	1
	1.476 kWh	100%	2
	1.607 kWh	100%	2
	0.115 kWh	100%	2

Experiment Variables

Dependent Variable

The primary dependent variable is energy consumption in kilowatt-hours (kWh). This was continuously collected at 1-minute intervals throughout all phases of the experiment. However, 15-minute intervals were used for all analyses as it best replicates smart meter transmission intervals ("FERC: Industries—Demand Response," 2019). Cumulative energy consumption was also measured for each collection period.

Additionally, as a way of monitoring how escrow balances evolved over the treatment period, account balances were updated across all 15-minute time periods. Proxy escrow balances for the control group (P4P) were generated so as to better compare depletion over time and to facilitate comparing performance with the treatment group (EEE). In other words, the researcher could directly determine how each group was depleting their aggregate potential financial gains from the incentive. Individuals in the EEE group were able to monitor their own depletions, while those in the P4P group could only estimate.

Independent and Control Variables

A pre-experiment survey was conducted prior to any data collection in order to collect sociodemographic information and self-reporting attitudes and history toward energy use. These data were primarily used as control variables, but also to use as interaction variables in instances where sociodemographic, attitudes, and history have been shown to affect energy behavior. Figure 20shows the survey questions that all participants were required to complete prior to the study orientation briefings.

One control variable that was not included was ambient temperature. This was omitted for two reasons, 1) all rooms in the residence halls are centrally controlled, and 2) campus policy forbids the use of space heaters in residence halls. Although the use of fans is not prohibited, it was decided that the low power requirements and low use would not require a unique ambient temperature control requirement.

Sociodemographic variables

These variables included, gender, age range, academic status, residence hall, room occupancy, and whether all room occupants were participants in the study. These are included because there is some evidence to suggest that energy and pro-environmental outcomes have sociodemographic correlations. However, theoretical linkages to prospect theory are not known or well-understood. Figure 21 shows the aggregated results of the sociodemographic questions.

Energy use self-assessment and Knowledge variables

These variables reflected previous household experience with energy use as well as self-evaluation of energy usage habits and knowledge. Figure 22 shows the summary of all responses.

GMU/Dickinson College Energy Consumption Study Pre-Survey

* Required

1. **Email address** *

2. **Dickinson College email address (if different from above)**

3. **Name** *

4. **Gender** *
   Mark only one oval.
   - ⬭ Female
   - ⬭ Male

5. **Age** *
   Mark only one oval.
   - ⬭ 18-20
   - ⬭ 20-22
   - ⬭ > 22

6. **Academic Status** *
   Mark only one oval.
   - ⬭ Freshman
   - ⬭ Sophomore
   - ⬭ Junior
   - ⬭ Senior

7. **Race** *
   Mark only one oval.
   - ⬭ Black or African American
   - ⬭ White
   - ⬭ American Indian and Alaska Native
   - ⬭ Asian
   - ⬭ Native Hawaiian and Other Pacific Islander
   - ⬭ Two or more races

8. **What is your major (If undecided, write "undecided")?** *

9. **Are you using financial assistance to help fund your education?** *
   Mark only one oval.
   - ⬭ Yes
   - ⬭ No

10. **Total household size of last residence (incl. self)** *
    Mark only one oval.
    - ⬭ 1
    - ⬭ 2-3
    - ⬭ 4-5
    - ⬭ >5

11. **What is the occupancy of the dorm room you are currently residing in?** *
    Mark only one oval.
    - ⬭ Single
    - ⬭ Double
    - ⬭ Three or more

12. **Are all occupants of your dorm room participating in the study** *
    Mark only one oval.
    - ⬭ Yes
    - ⬭ No
    - ⬭ Don't Know

13. **How would you characterize your energy usage relative to persons your age ?** *
    Mark only one oval.
    - ⬭ Much less than average
    - ⬭ A little less than average
    - ⬭ About average
    - ⬭ A little more than average
    - ⬭ Much more than average

14. **How would you characterize your knowledge regarding energy consumption relative to persons your age?** *
    Mark only one oval.
    - ⬭ Much less knowledgable than average
    - ⬭ A little less knowledgable than average
    - ⬭ About average
    - ⬭ A little more knowledgable than average
    - ⬭ Much more knowledgable than average

15. **In a typical dormitory room, how significant is lighting relative to the entire energy load?** *
    Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very small	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Very large

16. **In a typical dormitory room, how significant is space heating/cooling relative to the entire energy load?** *
    Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very small	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Very large

17. **In a typical dormitory room, how significant are plug loads (e.g. computers, TV, etc) relative to the entire energy load?** *
    Mark only one oval.

	1	2	3	4	5	6	7	8	9	10	
Very small	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	Very large

Figure 20: Pre-experiment Survey (all participants)

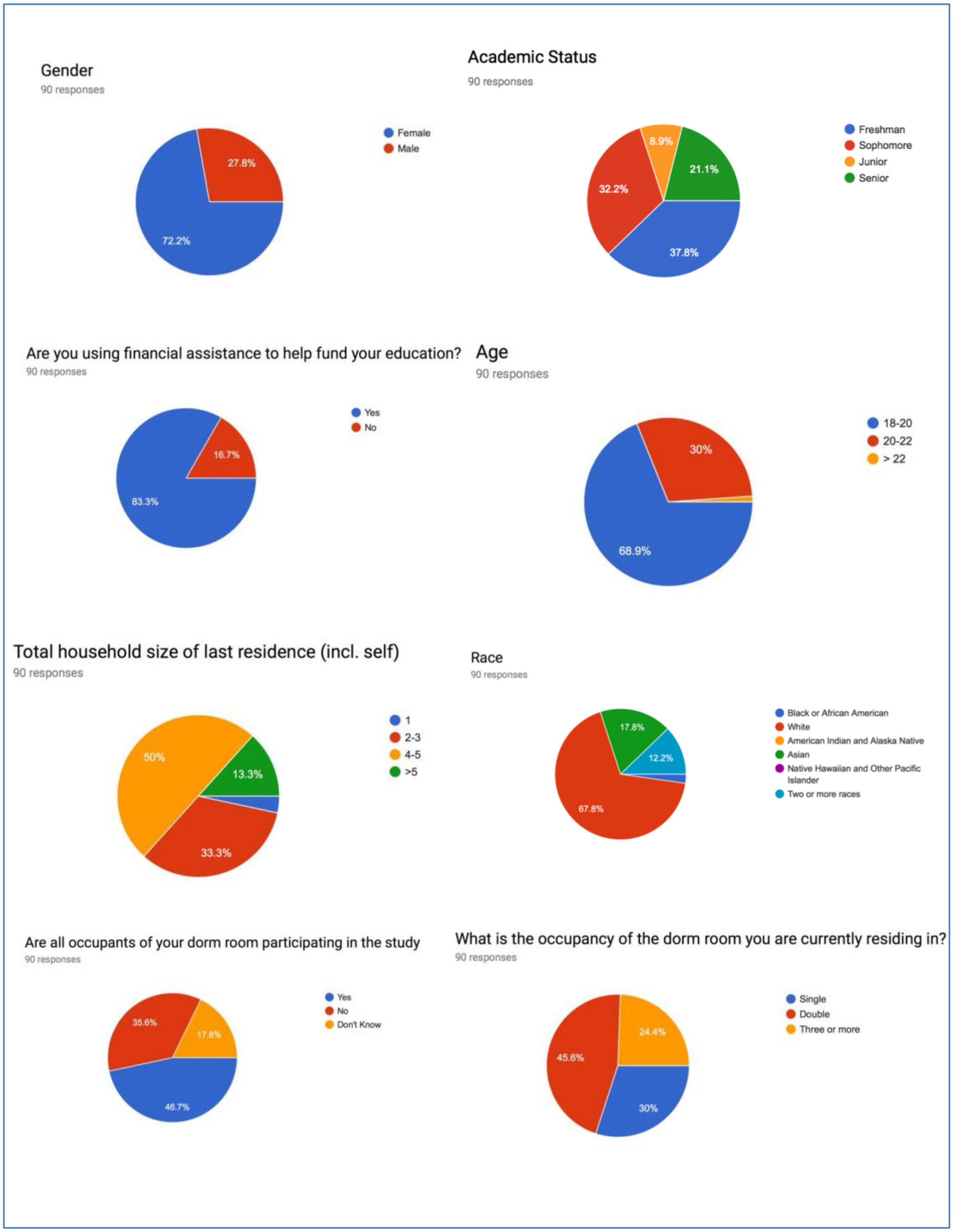


Figure 21: Summary of Sociodemographic Results of Pre-experiment Survey

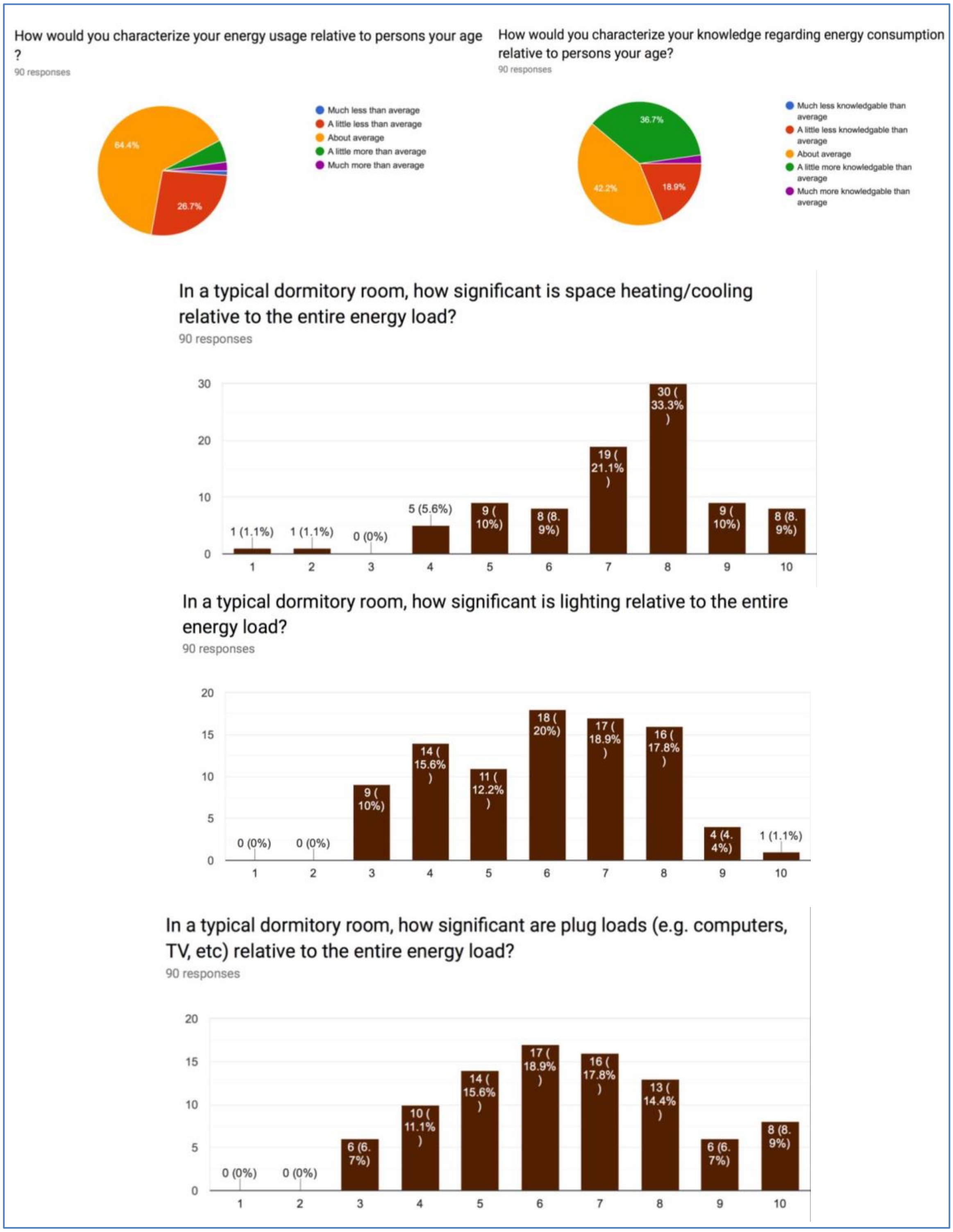


Figure 22: Energy use self-assessment and Knowledge Results

Baseline Energy Usage

In order to establish an incentive structure that was reflective of each student's average energy use, a baseline collection period of 28-days (Feb 8 - Mar 8) was used as the reference period. These data were used to inform what the potential financial reward would be for each student. In the case of the EEE treatment group, the average daily use during the baseline period was projected through the entire treatment period assuming that student used no energy. Since the baseline and treatment collection periods were exactly 28 and 49 days, respectively, the initial EEE balance was calculated as shown in Equation 3.

Equation 3: Calculation of Initial EEE balances

$$EEE_{Initial\ balance} = \ Daily\ Avg.Usage\ (kWh)_{baseline} * \left(\frac{49}{28}\right) * \$1/(1\ kWh)$$

For both control and treatment groups, each student's average baseline energy use was fixed on the energy history tab of the GOEFER app. The user had the ability to view either daily, weekly, or monthly usage, with the average baseline energy use automatically adjusting for desired time period.

Baseline energy usage was needed to establish potential financial reward incentives, but also to ensure control and treatment groups were homogenous, as well as to determine if there was variation in behavior amongst light and heavy energy users.

Post Experiment Survey

A post experiment survey was essential to determine several factors. Figure 23 and Figure 24 are the surveys given to the control (P4P) and treatment (EEE) groups, respectively. Slightly different versions were given to each group to understand how the differing incentive frameworks may have affected each student's behavior. Results of this survey are presented in the next chapter.

GMU/Dickinson College Housing Study Post-Survey (PFP)

* Required

1. **How often did you check the GOEFER app to monitor your energy use?** *
   Mark only one oval.
   - Hourly
   - Daily
   - Weekly
   - Monthly
   - Less frequently than monthly
   - I never checked the app

2. **How significant was the financial incentive in reducing your energy use** *
   Mark only one oval.
   - Very significant
   - Somewhat significant
   - Not at all significant

3. **How would you characterize your final reward?** *
   Mark only one oval.
   - Much more than I expected
   - Somewhat more than I expected
   - About what I expected
   - Somewhat less than I expected
   - Much less than I expected

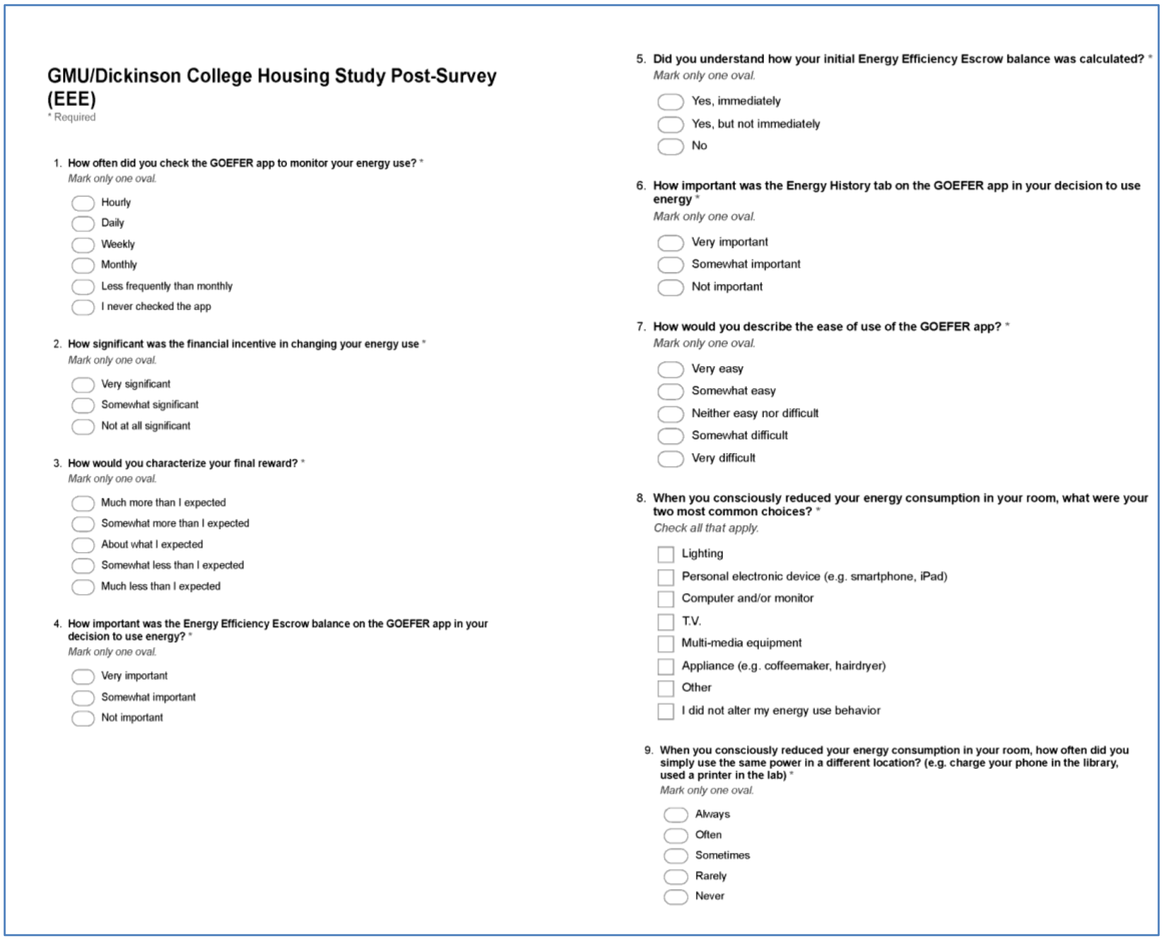
4. **How important was the Energy History tab on the GOEFER app in your decision to use energy?** *
   Mark only one oval.
   - Very important
   - Somewhat important
   - Not important

5. **How would you describe the ease of use of the GOEFER app?** *
   Mark only one oval.
   - Very easy
   - Somewhat easy
   - Neither easy nor difficult
   - Somewhat difficult
   - Very difficult

6. **When you consciously reduced your energy consumption in your room, what were your two most common choices?** *
   Check all that apply.
   - Lighting
   - Personal electronic device (e.g. smartphone, iPad)
   - Computer and/or monitor
   - T.V.
   - Multi-media equipment
   - Appliance (e.g. coffeemaker, hairdryer)
   - Other
   - I did not alter my energy use behavior

7. **When you consciously reduced your energy consumption in your room, how often did you simply use the same power in a different location? For example, charge your phone in the library** *
   Mark only one oval.
   - Always
   - Often
   - Sometimes
   - Rarely
   - Never

Figure 23: Post Experiment Survey (P4P)



GMU/Dickinson College Housing Study Post-Survey (EEE)
* Required

1. **How often did you check the GOEFER app to monitor your energy use?** *
Mark only one oval.
- Hourly
- Daily
- Weekly
- Monthly
- Less frequently than monthly
- I never checked the app

2. **How significant was the financial incentive in changing your energy use** *
Mark only one oval.
- Very significant
- Somewhat significant
- Not at all significant

3. **How would you characterize your final reward?** *
Mark only one oval.
- Much more than I expected
- Somewhat more than I expected
- About what I expected
- Somewhat less than I expected
- Much less than I expected

4. **How important was the Energy Efficiency Escrow balance on the GOEFER app in your decision to use energy?** *
Mark only one oval.
- Very important
- Somewhat important
- Not important

5. **Did you understand how your initial Energy Efficiency Escrow balance was calculated?** *
Mark only one oval.
- Yes, immediately
- Yes, but not immediately
- No

6. **How important was the Energy History tab on the GOEFER app in your decision to use energy** *
Mark only one oval.
- Very important
- Somewhat important
- Not important

7. **How would you describe the ease of use of the GOEFER app?** *
Mark only one oval.
- Very easy
- Somewhat easy
- Neither easy nor difficult
- Somewhat difficult
- Very difficult

8. **When you consciously reduced your energy consumption in your room, what were your two most common choices?** *
Check all that apply.
- Lighting
- Personal electronic device (e.g. smartphone, iPad)
- Computer and/or monitor
- T.V.
- Multi-media equipment
- Appliance (e.g. coffeemaker, hairdryer)
- Other
- I did not alter my energy use behavior

9. **When you consciously reduced your energy consumption in your room, how often did you simply use the same power in a different location? (e.g. charge your phone in the library, used a printer in the lab)** *
Mark only one oval.
- Always
- Often
- Sometimes
- Rarely
- Never

Figure 24: Post Experiment Survey (EEE)

Variable List

Table 6 and Table 7 shows the complete variable list for the baseline and treatment period analyses, respectively.

Table 6: List of variables - Baseline Period and Pre-Study Survey

Variable Name	Type	Coded	Specification	Description	Note
genderdum	Dummy		M(0) F(1)		
kwh	Continuous			energy in kilowatt-hours consumed during 15 minute interval	levels indicate total energy for all powerstrips assigned to each student
kwh_cum	Continuous			cumulative energy in kilowatt-hours consumed for the time period of interest	levels indicate total energy for all powerstrips assigned to each student
age	Categorical	1	18-20	Age in Years	
		2	20-22		
		3	>22		
acad_yr	Categorical	1	Freshman	Academic Status	
		2	Sophomore		
		3	Junion		
		4	Senior		
race	Categorical	1	White	2019 Dept. of Commerce race categories were used on suvey.	American Indian and Alaska Native and Native Hawaiian and Other Pacific Islander selections were on survey but yielded no responses
		2	Black or African American		
		3	Asian		
		4	Two or more races		
assist	Dummy		Not Receiving(0) Receiving(1) Financial Assistance	Are you using financial assistance to help fund your education?	No specific source or amount was indicated on question
lasthouse	Categorical	1	1	Total household size of last residence (incl. self)	
		2	2 or 3		
		3	4 or 5		
		4	>5		
dorm_size	Categorical	1	Single	What is the occupancy of the dorm room you are currently residing in?	
		2	Double		
		3	Three or More		
share	Categorical	1	No	Are all occupants of your dorm room participating in the study	
		2	Yes		
		3	Don't Know		
estownuse	Categorical	1	Much less than average	How would you characterize your energy usage relative to persons your age?	
		2	A little less than average		
		3	About average		
		4	A little more than average		
		5	Much more than average		
estownknow	Categorical	1	A little less knowledgable than average	How would you characterize your knowledge regarding energy consumption relative to persons your age?	"Much less knowledgable than average" was on the survey but yielded no responses
		2	About average		
		3	A little more knowledgable than average		
		4	Much more knowledgable than average		
devices	Categorical	1	1	Number of powerstrips issued	
		2	2		
		3	3		
EEE	Dummy		Control Group P4P (0) Treatment Group EEE (1)		
lighting	Continuous	1-10		In a typical dormitory room, how significant is lighting, space heating/cooling, lighting relative to the entire energy load?	
space					
plug					

Table 7: List of Variables - Treatment Period and Post-Study Survey

Variable Name	Type	Coded	Specification	Description	Note
appease	Categorical	1	Very easy	How would you describe the ease of use of the GOEFER app?	"Very Difficult" was on the survey but yielded no responses
		2	Somewhat easy		
		3	Neither easy nor difficult		
		4	Somewhat difficult		
importfin	Categorical	1	Not at all significant	How significant was the financial incentive in changing your energy use	
		2	Somewhat significant		
		3	Very significant		
finrwd	Categorical	1	Much less than I expected	How would you characterize your final reward?	
		2	Somewhat less than I expected		
		3	About what I expected		
		4	Somewhat more than I expected		
		5	Much more than I expected		
tabimport	Categorical	1	Not important	How important was the Energy History tab on the GOEFER app in your decision to use energy	
		2	Somewhat important		
		3	Very important		
escimport	Categorical	1	Not important	How important was the Energy Efficiency Escrow balance on the GOEFER app in your decision to use energy?	Question only posed to treatment group (EEE)
		2	Somewhat important		
		3	Very important		
useapp	Categorical	1	daily	How often did you check the GOEFER app to monitor your energy use?	"Hourly" was on the survey but yielded no responses
		2	weekly		
		3	monthly		
		4	less frequently than monthly		
		5	I never checked the app		
escimport	Categorical	1	Not important	How important was the Energy Efficiency Escrow balance on the GOEFER app in your decision to use energy?	Question only posed to treatment group (EEE)
		2	Somewhat important		
		3	Very important		
migrate	Categorical	1	Never	When you consciously reduced your energy consumption in your room, how often did you simply use the same power in a different location? (e.g. charge your phone in the library, used a printer in the lab)	
		2	Rarely		
		3	Sometimes		
		4	Often		
		5	Always		
		6	I never altered the way I used energy		
escunder	Categorical	1	No	Did you understand how your initial Energy Efficiency Escrow balance was calculated?	
		2	Yes, but not immediately		
		3	Yes, immediately		

Control and Treatment Group Formation

Care was taken to make each group as homogenous as possible across each criteria below in order of decreasing importance.

a) Housing unit (single/double/>3) – The objective was two-fold, 1) to have an equal number of persons in each of the three distinct room configurations, and 2) to ensure all persons within the same room configuration were in the same group. The latter criteria minimizes the possibility that students might speculate on the purpose of the experiment and, thus, to minimize expectancy effects.

b) Baseline energy usage – As noted earlier, there is empirical evidence from residential utility behavioral programs that some behaviors are correlated to baseline levels of usage. Students were sorted by quintile and assigned randomly to each group.

c) Academic Year

d) Gender

As can be seen in Table 8, control (P4P) and treatment (EEE) groups were perfectly balance between three of the four criteria with only a small, irreconcilable difference in academic year.

Table 8: Randomization Table for Control and Treatment Groups based on selected Criteria

	Baseline Energy Use (kWh)						Room Size			Academic Year				Gender	
	Total	1 (top 20%)	2	3	4	(bottom 20%	Single rooms	Double rooms	3>	F	Soph	J	Senior	M	F
EEE	568	9	9	9	9	9	14	20	11	17	16	4	8	12	33
PFP	528	9	9	9	9	9	13	21	11	17	13	4	11	13	32

Administration of Treatment

The treatment period ran for 49 days, from March 18 (0400 UTC/GMT – 0000 EDT) until May 6 (0400 UTC/GMT -- 0000 EDT). Email announcements were sent to each student at midnight (new day) March 18. A separate incentive announcement went out to each group. The control (P4P) and treatment (EEE) group emails are in Figure 25 and Figure 26, respectively.

Participants - Over the past several weeks we have calculated your average daily power usage. Starting on March 18 and based on your use over the next 49 days (7 weeks) we will reward you with $1 for every kWh you use below your average, which will be reflected in the “Energy History” tab of your updated GOEFER app (v 1.0.2).

For instance, if your average daily power usage was 1.0 kWh/day and decreased to 0.9 kWh/day over the next 49 days your reward would be:

(1.0 – 0.9) kWh/day X (49 days) X ($1.0 reward/(kWh)) = $4.90

This amount will be added to your $25 participation fee at the end of the year. If you use more than your average daily use, you will not receive any additional compensation beyond your participation fee.

Figure 25: Announcement for Financial Incentive (P4P)

Participants - Over the past several weeks we have calculated your average daily power usage. Starting on March 18 and based on your use over the next 49 days (7 weeks) we will reward you with $1 for every kWh you use below your average, which will be reflected in the “Energy History” tab of your updated GOEFER app (v 1.0.2).

Based on this reward incentive your app will automatically calculate the maximum compensation to which you are entitled *if you were to use no power for the next 49 days.* This is your energy efficiency escrow (EEE) account and will appear on the GOEFER app home screen.

For instance, if your average daily power usage was 1.0 kWh/day your EEE will reflect a starting balance of:

(1.0 kWh)/day X (49 days) X ($1.0 reward/(kWh)) = $49.0

Your EEE will continuously decrement based on your actual usage. For instance, if after 49 days your average daily usage decreased from 1.0 kWh/day to 0.9 kWh/day your EEE will show a balance of:

(1.0 – 0.9) kWh/day X (49 days) X ($1.0 reward/(kWh)) = $4.90

Whatever amount remains in your EEE will be added to your $25 participation fee at the end of the year. If you deplete the balance in your EEE, it will remain at $0.00 and you will not receive any additional compensation beyond your participation fee.

Figure 26: Announcement for Financial Incentive (EEE)

Students were then required to immediately update their GOEFER app in order for several new features to appear that would assist them in monitoring their usage relative to the incentive. Figure 27 shows two of those features. All students now saw a new bar in the energy history tab labeled “Avg.”. This reflected each student’s average energy use (either by day, week, or month, as selected) as calculated during the baseline collection period. The treatment group (EEE) had an additional feature, labeled “EE Escrow”. This would appear on all tabs in the same relative position. Just as reflected in the email incentive send to the treatment group, the EEE balance would be continuously decremented based on the rate of each student’s energy use.

One consideration for the administration of the incentive for the control group (P4P) was whether to periodically update them on what their potential reward would be as the treatment period progressed. It was decided that no information other than that provided on the Energy History Tab would be included. The rationale was that updates of potential gains may itself induce a loss aversion reaction. Thus, control group students had to rely entirely on their own cognitive abilities to estimate what their final reward would be throughout the entire treatment period.

Similarly, it was decided that, aside from the emails announcing the incentive, no reminders would be sent to participants about the incentive. It was expected that some level of user experience would be required for some members of the treatment group (EEE) to understand how the EEE worked despite the example given in the initial email.

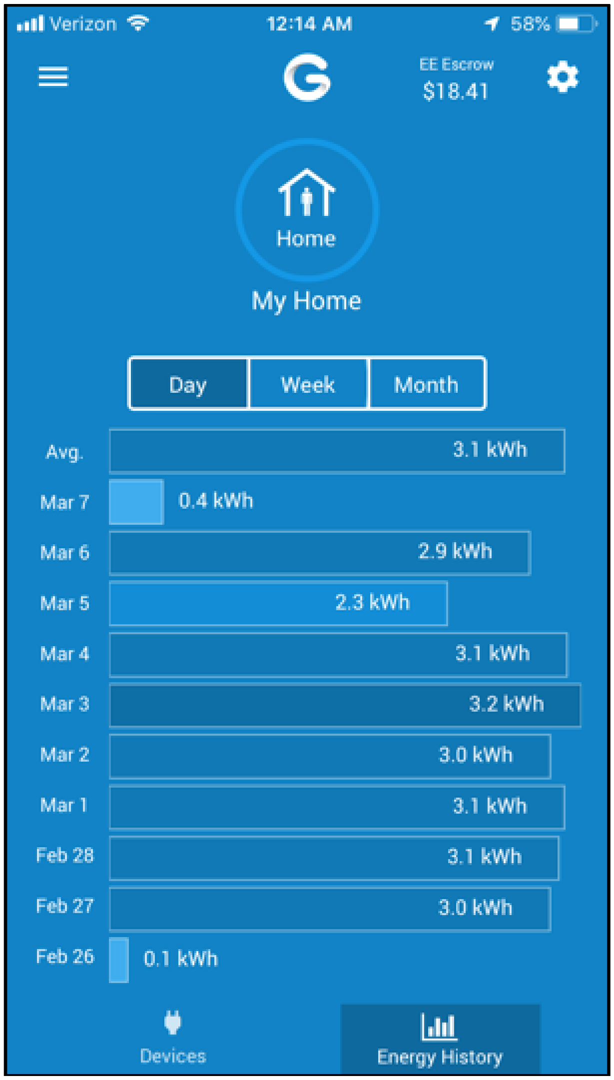


Figure 27: Incentive Features reflected on GOEFER app

FIELD EXPERIMENT RESULTS

This section provides both primary and secondary observations of the experiment.

Student Response to Project

The preponderance of study respondents, 76 (out of 90), were drawn from the Fall recruitment. 60 of those 76 respondents (or 78.9 percent) were female. Data provided by the Residence Life and Housing office show recruitment emails went out to 1,260 eligible students. Table 9 shows gender data for all on campus student residents.

Table 9: Gender Distribution for Recruitment Population

Gender	Freq.	Percent	Cum.
F	683	53.44	53.44
M	595	46.56	100.00

A binomial test shows that we can reject the null hypothesis that the proportion of females in the study is the population frequency of 53.44 percent ($p < 0.05$).

The balance of the final sample population of 90 students came from direct classroom recruiting. This included 19 additional students[26].

[26] Five of the original Fall recruits enrolled in a Study Abroad program and were, thus, not available for the treatment period. None of the data collected from those individuals was used.

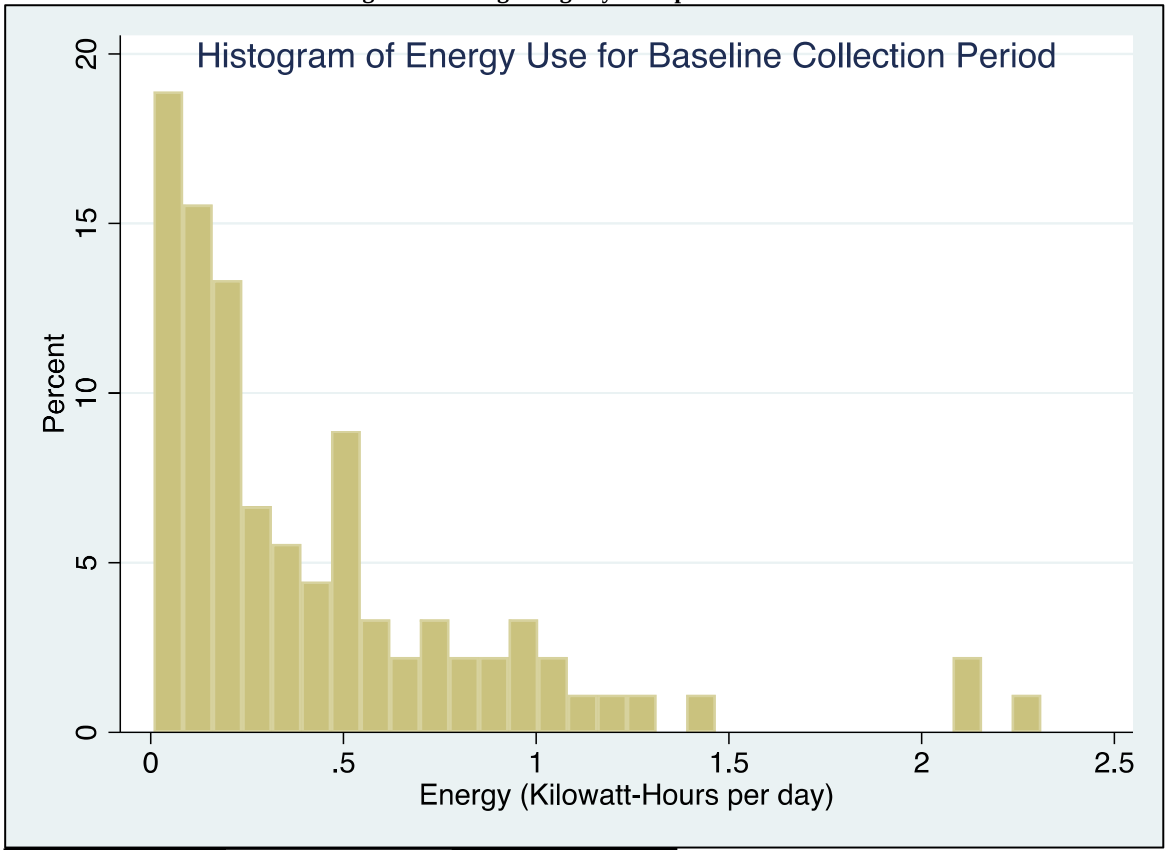
Baseline Collection

A 28-day collection period was used to establish personal baselines for each student. Energy usage was archived every 15-minute for all participants. Average daily usage was used in order to accommodate the few dropouts that occurred during the period. There were 2,688 (28*4*24) collection opportunities for this period. 85 of the 90 students experienced zero collection dropouts during the period[27]. For any daily period where a full 96 (24 X 4) possible values were not collected on any student, their average for what was collected for a given day was normalized to a full 24-hour period. This approximation was valid given the asynchronous use of a typical student throughout the day. The 24-hour normalization allowed for more accurate comparisons between students and the inclusion of a higher percentage of panels.

Students were not told the parameters of the baseline collection period so as to minimize biases. A total energy usage of 1094 kWh was measured for the baseline period. Table 10 shows the distribution of energy usage – for the entire sample population (Mean = 0.434) and (Standard Deviation = 0.472) as well as by group.

[27] The remaining five had collections of 2280, 2529, 2603, 2645, and 2675.

Table 10: Baseline Collection Histogram and Avg. Usage by Group



Group	mean	sd
P4P	.415	.432
EEE	.452	.513
Combined	.434	.471

Clearly, these daily electricity consumption levels fall considerably short of typical U.S. residential levels, which, according to the EIA average about 28.9 kWh per day (Energy Information Administration). However, given that these levels are based on a single room, per person (versus per household), and not measuring space heating/cooling or lighting, the data is representative of a load set that is highly individualized, aiding to the objectives of the experiment.

These baseline data also provide a rationale for why the energy reduction incentive had to be higher than market rates. For instance, based on an incentive of $0.10 per kWh saved, the mean potential savings (if *no* energy was consumed) would be $2.13. This potential reward was unlikely to overcome the cost of paying attention. Thus, to make the incentive more representative of what a typical household decision-maker might face, as well as to conform to the study's budget constraints, the incentive was set at $1 per kWh saved. This amounted to an average EEE balance -or- an average potential reward for the P4P group of $21.26.

It is also worth noting that the standard deviations of the study's sample population are somewhat larger than most reliable data on residential household use. For a wide sampling of different households in Portugal, standard deviations ranged from about a quarter to half of the sample mean. Standard deviation in the U.S. tend to approach about 15 percent of mean (Pombeiro, Pina, & Silva, 2012). Because the types of loads being measured with the power strips are highly variable and taste specific, and thus not dependent on basic comfort needs of space heating/cooling and lighting, a higher standard deviation was expected, although not predictable. Thus, these baseline data provide useful insights in understanding energy use patterns in environments such as college campuses and shared housing units where large energy loads are centrally controlled.

Sociodemographic and Background Factors on Baseline Usage

Table 11 shows the clustered, pooled-regression results for the baseline collection period. Equation 4 shows the daily-average-usage OLS model using student clustering to ensure robust standard errors and accurate p-values are used. Table 12 expands results across factor variables. Independent variables that showed increased baseline usage were white and male students. Energy usage decreased with increasing age group, with seniors showing the lowest and only statistically significant academic year group. Financial assistance was not statistically significant. White and non-white differentiation showed significance with respect to Black or African American and Asian race groups using less energy.

Students' estimation of their own energy consumption relative to other students revealed interesting discrepancies. For instance, students who stated they used "a little more than average" consumed considerably more energy than all other users. Those who revealed their own use to be "much more than average" used less energy than all responses with the exception of those who stated they used "much less energy than average". All results were statistically significant.

Students' self-assessment of their energy knowledge correlated very well with baseline level usage, much better than did their estimation of personal energy usage. This is consistent with the theory of planned behavior (TPB) that suggests the main determining factors of behavioral intention are attitudes, which are influenced by *knowledge* and experience. Again, all results were statistically significant.

Lastly, it was not surprising that those students who requested multiple power strips used more energy. Although some students suggested that they needed additional strips to accommodate a larger space with limited outlets, that translated into more actual load.

Equation 4: Clustered OLS model for Avg. Daily Usage (Baseline Period)

$$Daily\ Avg.Usage_{it} = \beta_0 + \beta_1 genderdum_{it} + \beta_2 acad\_yr_{it} + \beta_3 race_{it} + \beta_4 assist_{it}\ \beta_5 lasthouse_{it} + \beta_6\ dorm\_size_{it} + \beta_7\ share_{it} + \beta_8\ estownuse_{it} + \beta_9 estownknow_{it} + \beta_{10}\ devices_{it} + \varepsilon_{it}$$

Table 11: Clustered, Pooled-Regression Results of Baseline Collection Period[28]

kwh_daily	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
genderdum	-0.295	0.121	-2.43	0.017	-0.537	-0.054	**
acad_yr	-0.067	0.042	-1.60	0.113	-0.150	0.016	
race	-0.052	0.036	-1.44	0.154	-0.125	0.020	
assist	0.159	0.120	1.33	0.188	-0.079	0.398	
lasthouse	-0.064	0.044	-1.45	0.151	-0.152	0.024	
dorm_size	0.104	0.081	1.28	0.203	-0.057	0.264	
share	-0.009	0.067	-0.14	0.890	-0.142	0.124	
estownuse	0.129	0.070	1.84	0.069	-0.010	0.269	*
estownknow	-0.091	0.066	-1.38	0.171	-0.221	0.040	
devices	0.160	0.093	1.73	0.087	-0.024	0.344	*
Constant	0.298	0.411	0.72	0.471	-0.519	1.114	

Mean dependent var	0.433	SD dependent var	0.541
R-squared	0.192	Number of obs	2606.000
F-test	3.144	Prob > F	0.002
Akaike crit. (AIC)	3658.337	Bayesian crit. (BIC)	3722.858

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[28] To check for collinearity of variables, a VIF (Variance inflation factor) test was conducted with all independent variables < 2. Panels were clustered by individual students.

Table 12: Clustered, Pooled-Regression Results of Baseline Collection Period Across Factor Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	kwh_daily	kwh_daily	kwh_daily	kwh_daily	kwh_daily	kwh_daily
genderdum	-0.282**	-0.356***				
	(0.126)	(0.129)				
acad_yr	-0.046					
	(0.043)					
race	-0.058					
	(0.038)					
assist	0.151	0.064				
	(0.113)	(0.113)				
dorm_size	0.071					
	(0.077)					
share	-0.048					
	(0.066)					
devices	0.232**					
	(0.089)					
1bn.acad_yr						
2.acad_yr		-0.120				
		(0.120)				
3.acad_yr		0.159				
		(0.198)				
4.acad_yr		-0.258**				
		(0.099)				
1bn.race						
2.race		-0.227*				
		(0.134)				
3.race		-0.287***				
		(0.090)				
4.race		0.032				
		(0.130)				
1bn.dorm_size						
2.dorm_size		0.016				
		(0.093)				
3.dorm_size		0.210				
		(0.175)				
1bn.share						
2.share		0.047				
		(0.097)				
3.share		-0.095				
		(0.132)				
1bn.devices						
2.devices		0.206**				
		(0.088)				
3.devices		0.438*				
		(0.260)				
1bn.age						
2.age			-0.179***			
			(0.067)			
3.age			-0.255***			
			(0.055)			
1bn.lasthouse						
2.lasthouse				0.088		
				(0.206)		
3.lasthouse				0.135		
				(0.212)		
4.lasthouse				-0.071		
				(0.211)		
1bn.estownuse						
2.estownuse					0.321***	
					(0.059)	
3.estownuse					0.319***	
					(0.043)	
4.estownuse					0.885**	
					(0.363)	
5.estownuse					0.250*	
					(0.137)	
1bn.estownknow						
2.estownknow						-0.278**
						(0.123)
3.estownknow						-0.276**
						(0.111)
4.estownknow						-0.440***
						(0.133)
_cons	0.258	0.550***	0.410***	0.266	0.008***	0.582***
	(0.283)	(0.171)	(0.055)	(0.201)	(0.000)	(0.102)
Obs.	2606	2606	7094	7094	7094	7094
R-squared	0.140	0.221	0.031	0.021	0.080	0.056

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Treatment Period

The earlier Control and Treatment Group Formation section describes the prioritization of control and treatment group assignment. Figure 28 shows distribution among the variables prioritized for group balancing.

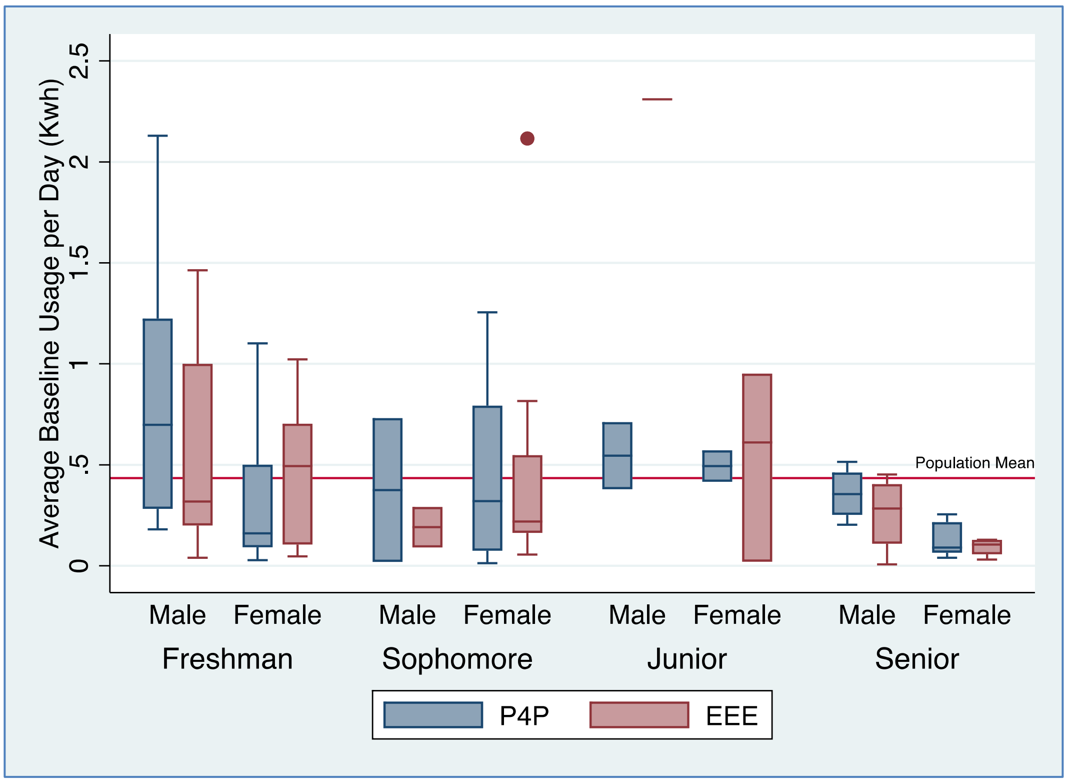


Figure 28: Boxplot of Sub-group distributions

A 49-day treatment period was used to collect energy use information after the start of the incentive. Again, energy usage was taken every 15-minutes for all participants and normalized to a 24-hour period. This amounted to 4705 observations per student[29]. Table 13 shows the distribution of energy usage – for the entire sample population (Mean = 0.307) and (Standard Deviation = 0.364). The total expected energy usage for the treatment period was calculated using the baseline period usage (1094 kWh) and multiplied by the fraction of days in each period (49/28) = 1915 kWh. The total energy used for the treatment period was 1354 kWh for a reduction of 561 kWh, or 29.3 percent.

Total student payouts for the incentive amounted to $679. This puts the effective payout per-kWh-saved at $679/561(kWh saved) = $1.21, since individuals were not penalized if they exceeded their baseline usage. Another way of stating this is to normalize the savings per dollar invested, thus showing an equivalent 29.3 percent/1.21 = 24.2 percent reduction in energy usage for every $1 of program rate-based incentive. This 5.1 percent delta can be regarded as the cost of allowing users who do not take advantage of the incentive to revert back to the mean of their normal usage. These users must be compensated for by energy savers.

Figure 29 shows a scatterplot of how the population varied their treatment period usage compared to their baseline energy usage. All those in green increased energy usage (28 users) relative to their baseline and represent consumption for which energy conservationists (62 users) had to overcome in order to reach the 29.3 percent reduction.

[29] Five students experienced some level of network outage, resulting in observations ranging from 3980 to 4700.

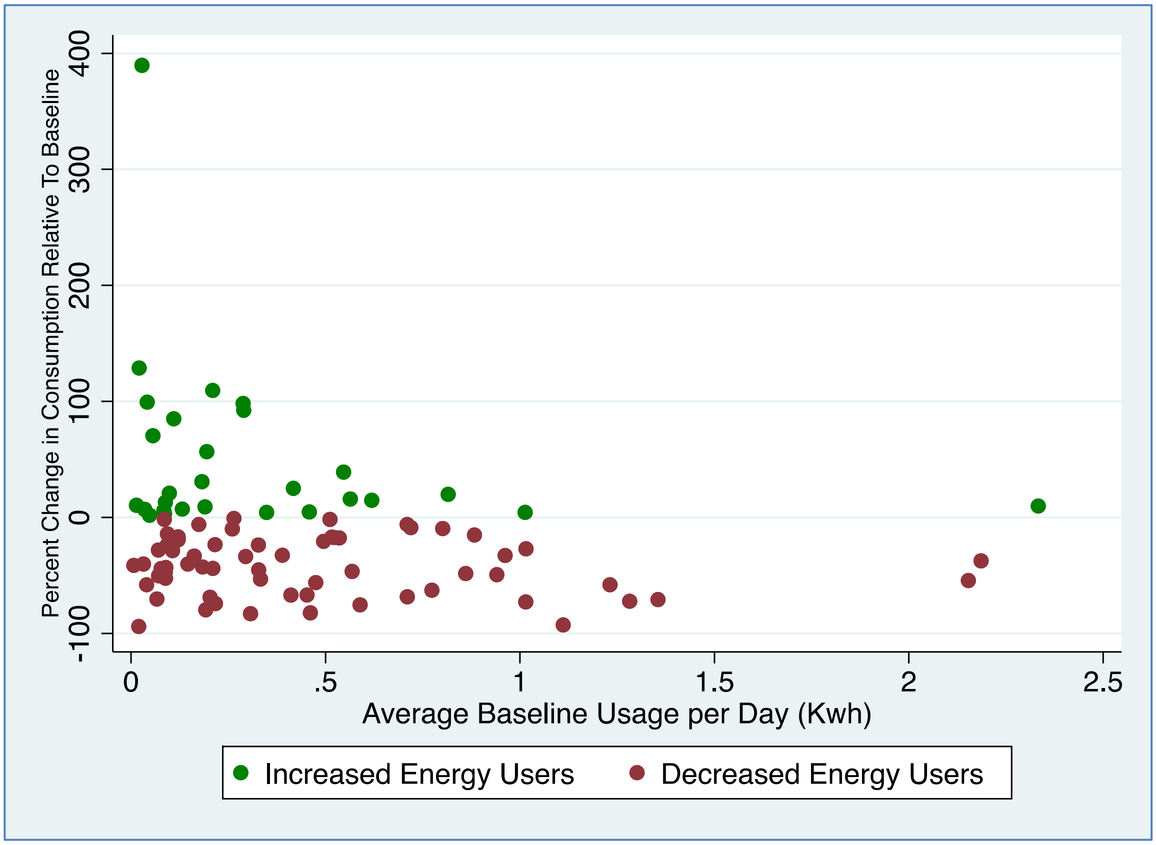
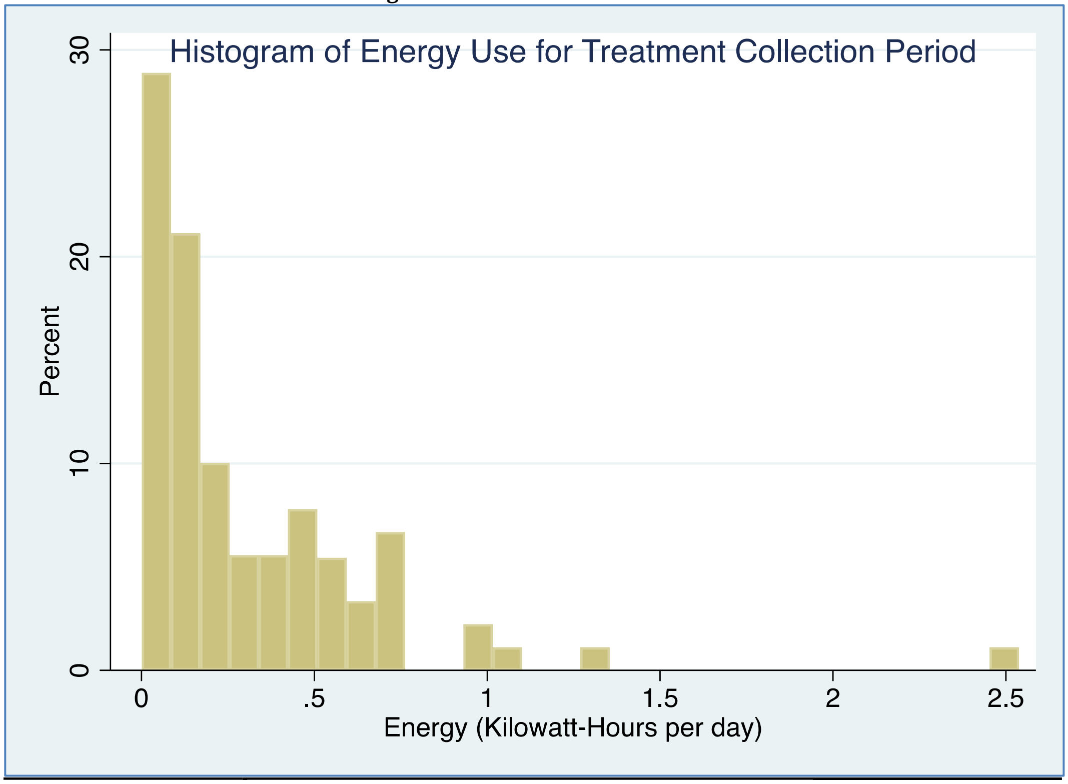


Figure 29: Comparison of Increased Usage vs. Decreased Treatment Usage by Baseline Usage

Table 13: Treatment Collection Histogram



Group	Mean (daily averages - Kwh)	sd
P4P	.252	.258
EEE	.362	.442
Combined	.307	.364

One way of understanding how the two groups performed relative to each other is to take the combined EEE balance of all participants in the treatment group (EEE) for each 15-minute interval and compare it the control group (P4P) assuming each participant had their own balance (Figure 30)[30]. Within two weeks after the treatment period

[30] In real-time 1-minute intervals were used to update the EEE escrow balances. The 15-minute and daily averages were derived from these data. Where outages occurred, the balances were restored by calculating users' historic averages. Interpolations or projections were not used when outages occurred. This accounts for the periodic "steps" in the graph.

commenced, the EEE group had already reduced their balances to below the level of the P4P group despite starting with a larger initial balance.

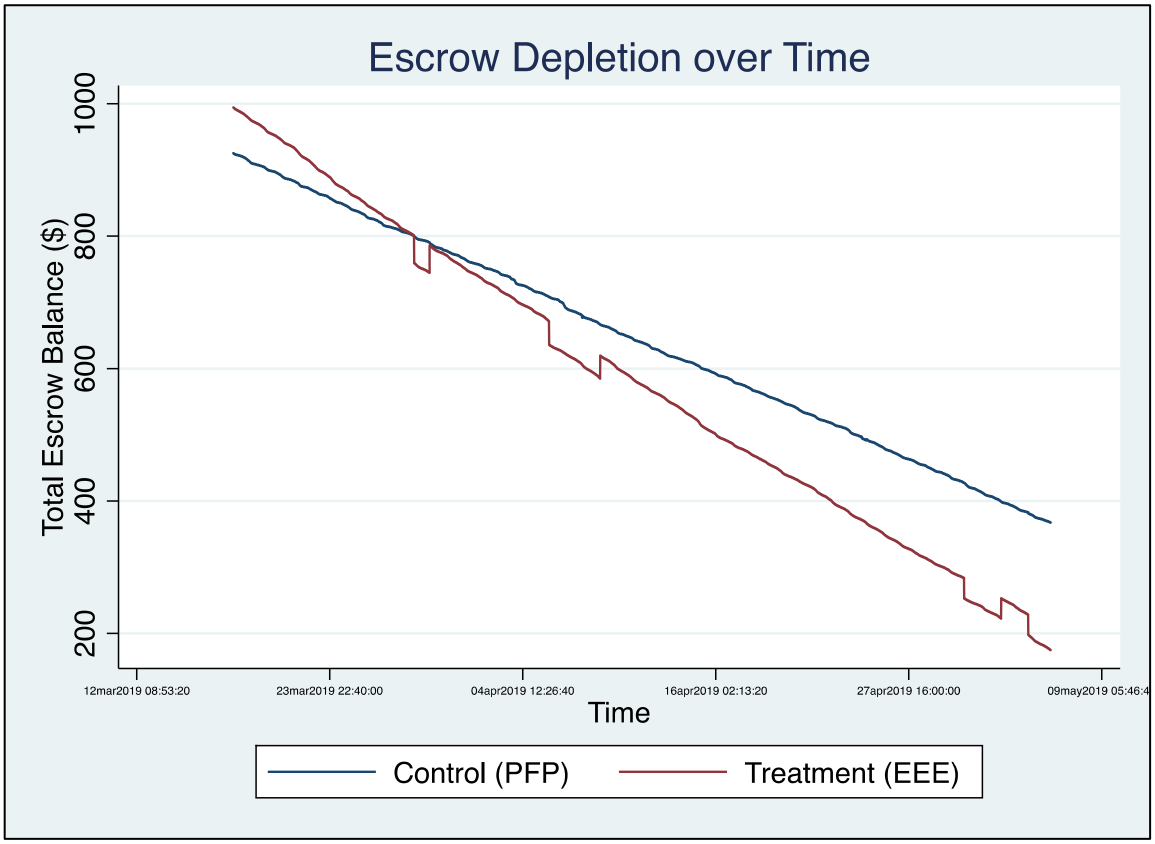


Figure 30: Escrow Depletion for Control and Treatment Groups

Analysis of Findings

Research Question #1

Research Question: Does the employment of a rate-based financial incentive reduce personal energy consumption?

Hypothesis: A financial incentive will reduce personal energy consumption across multiple frameworks (EEE and P4P).

Table 14 is a T test that compares the combined (unpaired) performance of both control (P4P) and treatment (EEE) groups relative to total baseline use.

Table 14: Unpaired T Test for All Groups - Baseline vs. Post-Treatment

	Baseline	Treatment	St_Err	p_value
avg daily use (Kwh)	0.434	0.308	0.030	0.000

Average daily consumption across both groups was reduced by 29.3 percent ($p < 0.001$). Clearly, we can, reject the null hypothesis that there is no difference in conservation outcomes based on a financial incentive.

Research Question #2

Research Question: Does the employment of an energy efficiency escrow (EEE) reduce consumption relative to the same financial incentive presented as a potential gain, modeled by a P4P program?

Hypothesis: The EEE incentive will result in lower energy consumption relative to the same financial incentive framed as a P4P program.

Table 15 shows a paired T test for each group's performance relative to their respective baselines. It shows average daily reductions of 39.2 percent ($p < 0.05$) and 19.9 percent ($p < 0.05$) in the P4P and EEE groups, respectively.

Table 15: Paired T Test for Each Group - Baseline vs. Post-Treatment

	Mean(Baseline Avg. daily use – Kwh)	Mean (Treatment Avg. daily use – Kwh)	St_Err	p_value
Control (P4P)	0.416	0.253	0.044	0.001
Treatment (EEE)	0.452	0.362	0.040	0.030

		Average Daily Energy Use (kWh)			
		Pre-Incentive	Post-Incentive	Difference	Difference-in-Differences
Group	P4P	0.416	0.253	0.163	0.073
	EEE	0.452	0.362	0.09	

Table 16 is a summary of observations of the pre and post-treatment summary of energy usage by group using *cumulative* energy levels. It is a difference-in-differences table comparing group means before and after treatments. Note the projection of usage for both groups without any treatment. This was done by taking the sum of the average daily usages of each group and multiplying it by the total number of treatment days (49 days)[31]. Figure 31 is a graphical display of Table 16.

Table 16: Difference-in-Differences summary table

	Cumulative Energy Use (kWh)				
	Baseline	Projected Use without Incentive	Post-Incentive	Difference	Difference-in-Differences
P4P	524.2	1441.6	1079.9	361.7	165.3
EEE	568.3	1562.8	1366.5	196.3	

[31] Despite the similarities this is not a standard difference-in-differences experiment in that there was not a third group with no financial incentive to account for time variant differences during the treatment period. However, the comparisons are still robust given the number of observations and the homogeneity between groups.

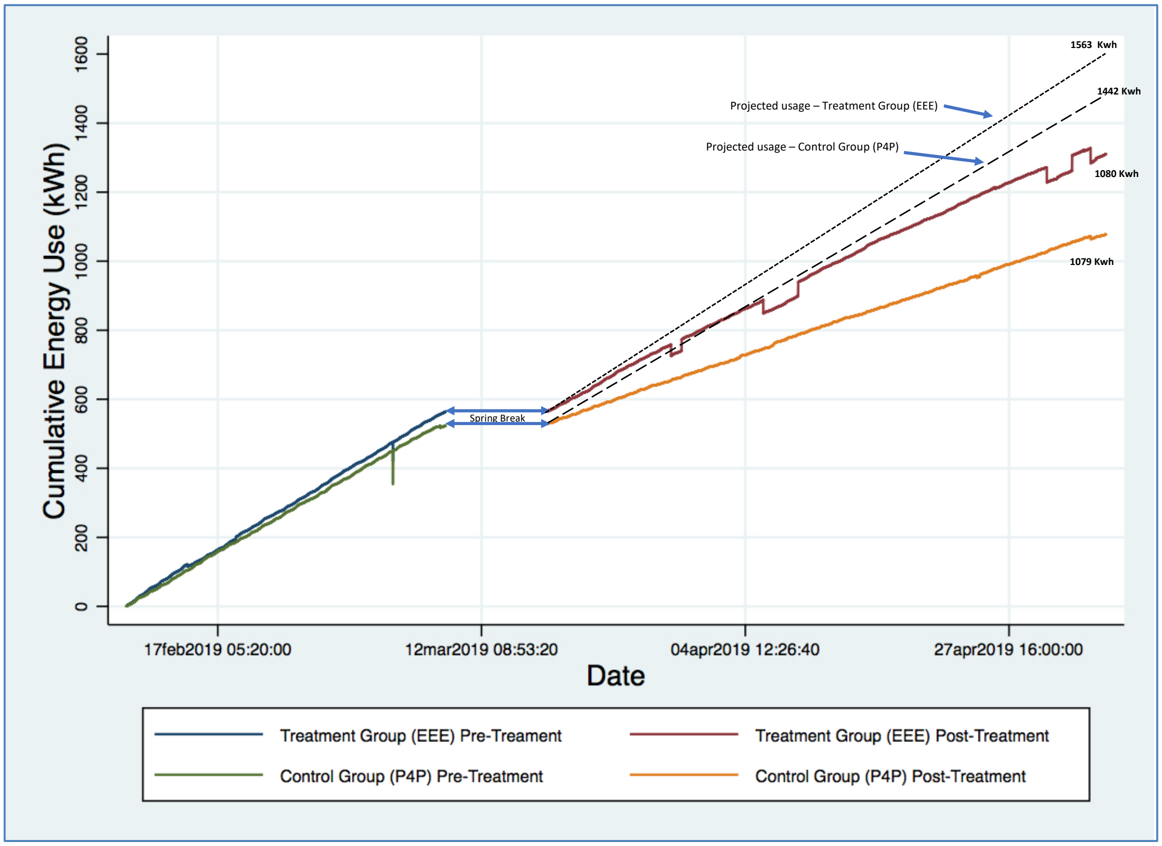


Figure 31: Difference in Post-Treatment and Estimated Usage for Control (P4P) and Treatment (EEE) Groups

The research hypothesis is refuted. The null hypothesis is rejected due to a statistically significant difference in the performance of the control group (P4P) over the treatment group (EEE).

In summary, this research shows that when consumers are continuously informed about their usage and offered an incentive to reduce consumption, those who are forced to cognitively calculate potential gains and are therefore forced to perform some form of risk management, perform better than those who are explicitly and continuously aware of their loss exposure.

Embedded in the research design itself is the acknowledgement that the EEE mechanism may not be well understood by all users. The post-study survey attempted to gauge user comprehension to determine how this might affect performance. The treatment group (EEE) had two additional questions that were specific to them (Figure 34) and (Figure 35). Several important observations emerged from these questions. First, the escrow bar on the GOEFER app was unique to the EEE group. Despite the fact that every user in that group had the ability to know *exactly* what their final compensation would be at the end of the performance period, only 57.8 percent responded that their reward was "about what I expected" (compared to 44.4 percent in the control (P4P) group). Although it was anticipated that a certain portion of the treatment group would not immediately understand exactly how the EEE worked, a third of them (33.3 percent) revealed they never did. It is reasonable to believe that the actual number might be slightly higher considering that some might be uncomfortable admitting it.

Second, 73.3 percent of treatment (EEE) group (compared to 68.9 percent in the control (P4P) group) participants responded that the Energy History Tab was either "very important" or "somewhat important" (Figure 32). So, despite having an explicit indicator of their reward potential, their behavior still seemed to divert toward their baseline usage comparison revealed in the Energy History Tab; *more so than even in the control group*.

An OLS model based on Equation 5 helps identify the singular effect of EEE understanding.

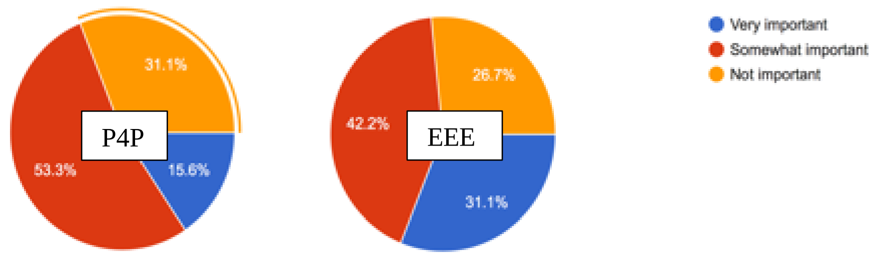


Figure 32: How Important was the Energy History Tab on the GOEFER app in your Decision to Use Energy?

Equation 5: Clustered OLS Model to Determine EEE Subgroup Effects

$$Daily\ Avg.Usage_{it} = \beta_0 + \beta_1 post_{treat_{it}} + \beta_2 i.escunder_{it} + \beta_3 post_{treat_{it}} * i.escunder_{it} + \varepsilon_{it}$$

Table 17 shows the results of the Equation 5 model. Relative to the control group (P4P), those who responded that they never understood how their EEE initial balance was calculated conserved far less energy than any other subgroup. In fact, individuals in that group tended to use *more* energy over the treatment period. This is made more clear in Figure 33, which shows the range of percent energy reductions by 4 groups, 1) the control group (P4P), and those in the EEE group who responded to the question “Did you understand how your initial EEE balance was calculated?” 2) No, 3) Yes, but not immediately, and 4) Yes, immediately.

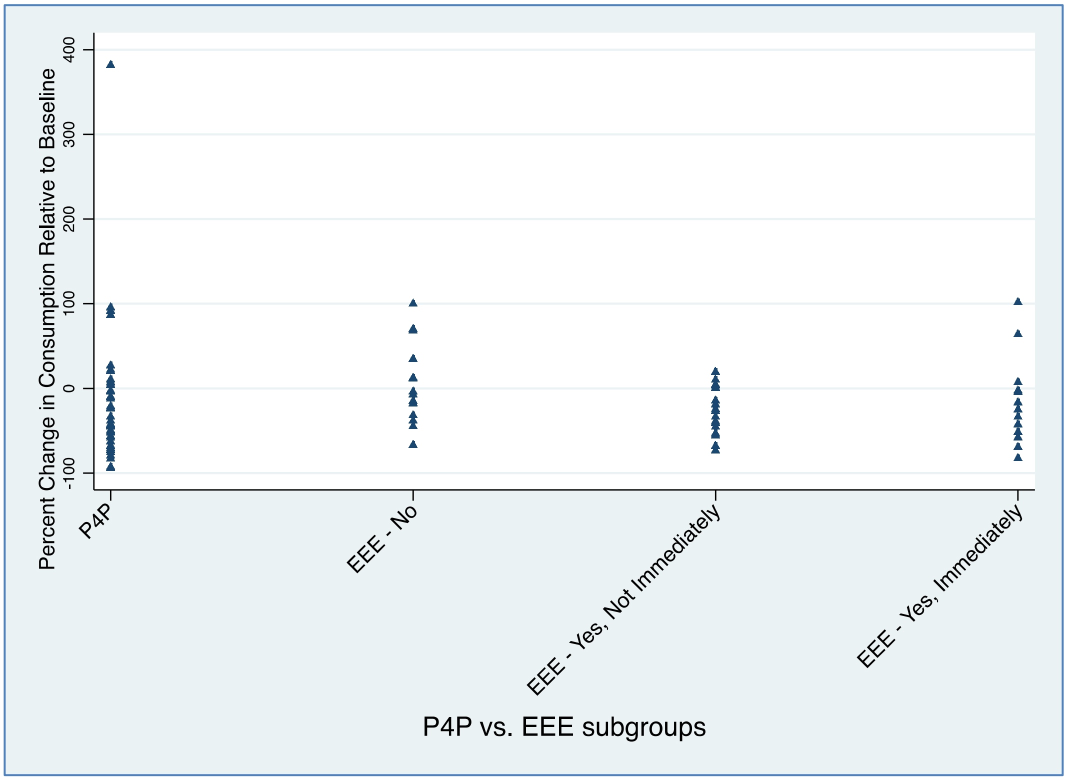


Figure 33: Reduction Comparison Between P4P and EEE Subgroups (Did You Understand How Your Initial EEE Balance was Calculated?)

Table 17: OLS Model of EEE (Subgroups) Post Treatment

kwh_daily	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
post_treat	-0.163	0.043	-3.78	0.000	-0.249	-0.077	***
P4P		.	.	.	.	.	
2.No	-0.125	0.083	-1.51	0.136	-0.291	0.040	
3.Yes, not immediately	0.288	0.181	1.59	0.115	-0.072	0.648	
4.Yes, immediately	-0.109	0.103	-1.05	0.294	-0.314	0.096	
P4P post_treat				.	.	.	.
1.post_treat#2.No	0.174	0.055	3.17	0.002	0.065	0.284	***
1.post_treat#3.Yes, not immediately	-0.024	0.100	-0.24	0.809	-0.223	0.175	
1.post_treat#4.Yes, immediately	0.090	0.057	1.57	0.119	-0.024	0.205	
Constant	0.416	0.064	6.49	0.000	0.288	0.543	***

Mean dependent var	0.354	SD dependent var	0.478
R-squared	0.077	Number of obs	7094.000
F-test	3.971	Prob > F	0.001
Akaike crit. (AIC)	9110.449	Bayesian crit. (BIC)	9165.386

**** p<0.01, ** p<0.05, * p<0.1*

This leads to an interesting observation. The effect of the EEE for those who did not understand how it was calculated was a significant barrier rather than an aid, or even a neutral factor, in conserving energy. This is true despite the fact that all persons in the EEE group still had the same tool (the energy history tab) that the P4P group had to monitor their usage.

As another check of user understanding of the EEE, it is useful to examine whether each student's assessment of their final reward correlated with their understanding of EEE balance determination. One would expect that if a student understood how the EEE balance was calculated, there final reward should not be subjective, but rather precise.

Table 18: Correlation Table of EEE User Understanding of Escrow Balance Determination vs. Final Reward

escrow understand	final reward					
	Much less than I expected	Somewhat less than I expected	About what I expected	Somewhat more than I expected	Much more than I expected	Total
No	1	3	9	2	0	15
	100.00	33.33	34.62	33.33	0.00	33.33
Yes, but not immediately	0	4	8	3	2	17
	0.00	44.44	30.77	50.00	66.67	37.78
Yes, immediately	0	2	9	1	1	13
	0.00	22.22	34.62	16.67	33.33	28.89
Total	1	9	26	6	3	45
	100.00	100.00	100.00	100.00	100.00	100.00

Table 18 is a correlation table of two survey question responses by EEE group members: 1) Did you understand how your initial Energy Efficiency Escrow balance was calculated? (Figure 34) and 2) How would you characterize your final reward? (Figure 36).

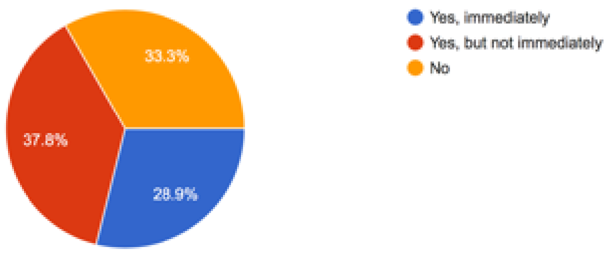


Figure 34: EEE group only - Did you understand how your initial Energy Efficiency Escrow balance was calculated?

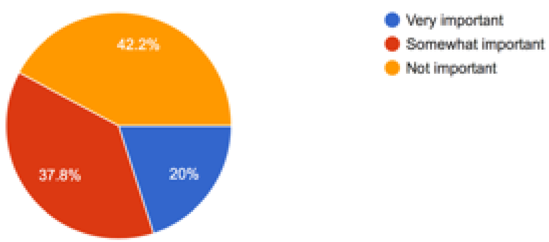


Figure 35: EEE group only - How Important was the Energy Efficiency Escrow balance on the GOEFER app in your Decision to use Energy?

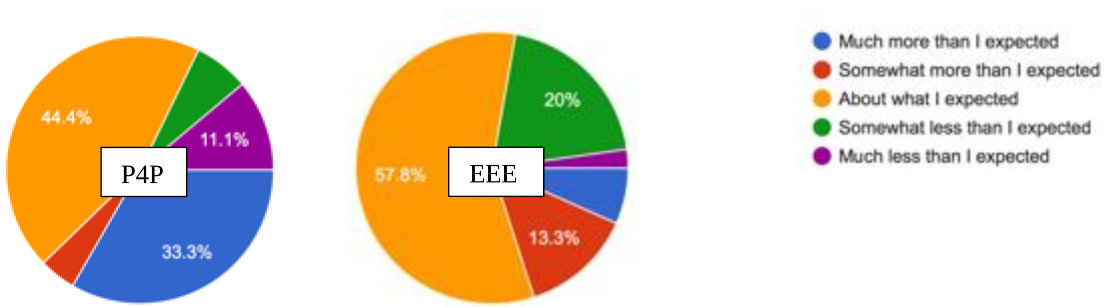


Figure 36: How Would you Characterize Your Final Reward?

The table clearly shows that those who understood how their EEE balance was calculated were no more likely to respond that their final reward was "about what I expected". Of course, some respondents may have characterized their final reward less in terms of being surprised at the final allocation as being reflective of its compensation parameters. Therefore, it is reasonable to conclude some may have not selected "about what I expected" when, in fact, it was exactly what they anticipated. This can be considered a missed opportunity in the post-survey brief to better understand consumers' assessments.

Table 19: Group Comparisons of Final Reward Estimations

Group	final reward					
	Much less than I expected	Somewhat less than I expected	About what I expected	Somewhat more than I expected	Much more than I expected	Total
P4P	5	3	20	2	15	45
	11.11	6.67	44.44	4.44	33.33	100.00
EEE	1	9	26	6	3	45
	2.22	20.00	57.78	13.33	6.67	100.00
Total	6	12	46	8	18	90
	6.67	13.33	51.11	8.89	20.00	100.00

Table 19 shows how each group (P4P and EEE) assessed the final reward amounts. A Pearson's Chi-Squared test confirms that we can reject the null hypothesis that the differences in the final reward estimates are statistically insignificant between the EEE and P4P group (Pearson chi2(4) = 16.45 Pr = 0.002)[32]. Overall, the P4P group assessed their reward as higher than expected with a full third revealing that the final reward was "much more than I expected".

Coupled with the fact that the P4P group conserved more energy, it supports the assertion that those participants "overshot" whatever conservation targets they may have set for themselves. It may also suggest that more utility could be gained with consumers

[32] Given the small f_e for some cell groups, a Fisher's exact test was also calculated with the same p = .002 value.

who obtain a higher compensation than they were expecting at the end of the performance period. This is significant because customer satisfaction is an important element in any utility-run program. Whether this is sustainable over multiple treatment periods is left to be verified for further research.

Research Question #3

Research Question: Do individuals with a higher potential reward for reducing energy, reflected in a higher baseline usage level, perform better relative than others?

Hypothesis: Individuals with a higher potential reward for conserving energy will reflect higher relative levels of energy reductions than those with lower potential rewards.

To address this question, the model used was simply to examine the daily average usage of each participant throughout the treatment period and then taking the percentage difference relative to their baseline average energy use (distribution shown in Table 10). This is analogous to comparing usage with each person's potential reward since the incentive was based on average baseline usage ($1 per kWh saved).

Equation 6: Percent Change in Average Energy Consumption Use

$$Percent\ reduction = \frac{(Avg.\ treatment\ usage - Avg.baseline\ usage)}{(Avg.baseline\ usage)}\ X\ 100$$

Equation 7: Clustered OLS model for Estimating Percent Reduction Relative to Baseline Avg. Usage

$$Percent\ Reduction_i = \ \beta_0 + \beta_1 Avg.Baseline\ Usage_i + \varepsilon_i \quad i = 1 - 90$$

Table 20: Clustered OLS model Results for Equation 7

Actual_perc	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Baseperday	-27.175	12.939	-2.10	0.039	-52.884	-1.465	**
Constant	-3.907	10.422	-0.38	0.709	-24.616	16.802	

Mean dependent var	-15.693	SD dependent var	61.492
R-squared	0.044	Number of obs	90.000
F-test	4.411	Prob > F	0.039
Akaike crit. (AIC)	995.777	Bayesian crit. (BIC)	1000.777

*** *p<0.01, ** p<0.05, * p<0.1*

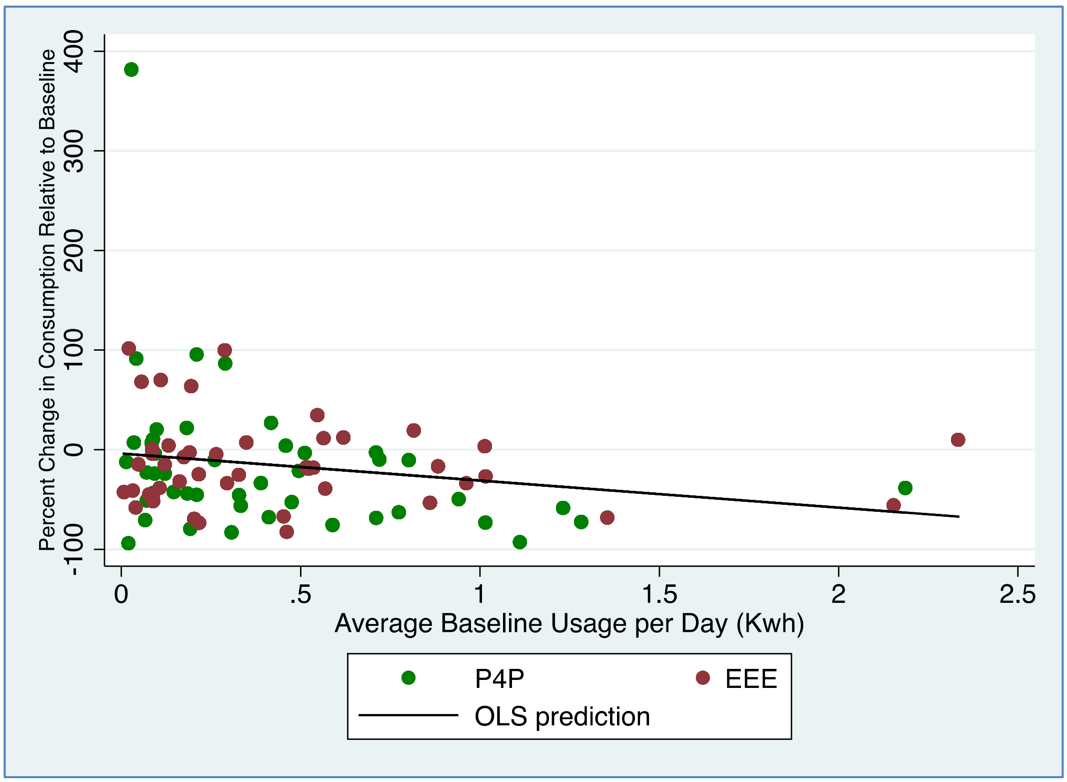


Figure 37: Energy Conservation Performance vs. Average Baseline Usage

The results of Table 20 show that we can reject the null hypothesis and conclude that as potential rewards increase, the relative percentage reduction in energy usage does increase. For every kWh per day increase in baseline usage, students reduced their consumption by 27.1 percent. The OLS model is shown in Figure 37 in concert with the scatterplot of control and treatment group usage results.

This finding has been observed over a handful of other DSM programs. Home energy reports (HERs), for instance, tend to have a stronger effect on heavy energy consumers as well (Allcott, 2011; Ayres et al., 2013). The magnitude of the reductions in this experiment, however, exceeds those seen in other energy reduction programs.

One reason could be that heavier energy users tend to have a higher number of discretionary loads to moderate. This would include loads that are not directly related to essential functions such as space heating/cooling and hot water heaters. Of course, this experiment examines only a small subset of overall residential household loads, with a large number of the plug-level loads likely being cycled without impacts to room comfort or hygiene.

Research Question #4

Research Question: Do levels of consumption reduction increase over time for the EEE?

Hypothesis: The EEE group will show greater levels of consumption reduction as the incentive period approaches its conclusion.

Although the consumption levels from the EEE group appear linear throughout the treatment period in Figure 31, a simple quadratic model was used to see if there was any noticeable non-linear effect.

Equation 8: OLS Model of Non-Linear Time Effects on Daily Average Energy Use for Treatment Group (EEE)

$$Daily\ Avg.Usage_{it} = \ \beta_0 + \beta_1 timeday^2{}_{it} + \beta_2 timeday_{it} + \varepsilon_{it}$$

Table 21: Clustered OLS Quadratic Model for EEE Group (Post-Treatment)

kwh_daily	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Time_squared	0.000	0.000	1.24	0.221	0.000	0.000	
timeday	-1.779	1.502	-1.19	0.243	-4.806	1.248	
Constant	19274.790	14110.521	1.37	0.179	-9163.095	47712.676	

Mean dependent var	0.363	SD dependent var	0.492
R-squared	0.002	Number of obs	2240.000
F-test	.	Prob > F	.
Akaike crit. (AIC)	3174.804	Bayesian crit. (BIC)	3186.233

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

With no effective coefficient in the "Time_squared" variable the hypothesis can be refuted. A slight linear reduction does exist over time reflecting increased conservation over time. However, the results are not statistically significant.

Post-Experiment Survey Results

Additional independent variables were derived from a post-experiment survey conducted immediately following the treatment period. Figure 42 and Figure 43 show the results of the survey for the control group (P4P) and treatment group (EEE), respectively.

The survey was also beneficial in determining how homogenous the behaviors were between control and treatments groups, especially with respect to interactions with the GOEFER app.

Sociodemographic and Background Factors on Energy Behavior Changes

The earlier section "Sociodemographic and Background Factors on Baseline Usage" examined factors that influenced baseline levels of usage. This section explores many of the same factors to determine their correlation(s), if any, on energy behavior performance. A series of T tests across several variables is appropriate since average daily baseline and average daily post-treatment energy levels can be directly compared.

Table 22: Paired T Test Results Pre-Post Treatment by Gender

	Baseline Mean (Avg. Kwh/day)	Post-Treatment Mean (avg. Kwh/day)	St_Err	p_value
Female	0.378	0.252	0.033	0.001
Male	0.580	0.444	0.064	0.044
	Percent Reduction relative to baseline			
Female	-14.000		7.881	0.081
Male	-20.096		11.366	0.090

Table 22 shows reductions across gender, with individual males reducing their energy usage by an average of 20.1 percent ($p < 0.1$) and individual females by 14.0 percent ($p < 0.1$). *Overall* male and female energy reduction was 23.4 percent and 33.3percent, respectively[33]. These seemingly contrasting results suggest that high level female baseline users resulted in a lot of the overall post-treatment mean reductions for females.

This result is not surprising in view of two previous finding, 1) females had lower levels of baseline energy use, and 2) research question #3 showed that higher baseline levels correlated with higher percentage reductions. Remember that overall energy

33 The differences in percentages *between* the two groups was not statistically significant.

savings was much higher due to the higher levels of reductions amongst heavier baseline users in general. Figure 38 shows this gender difference well.

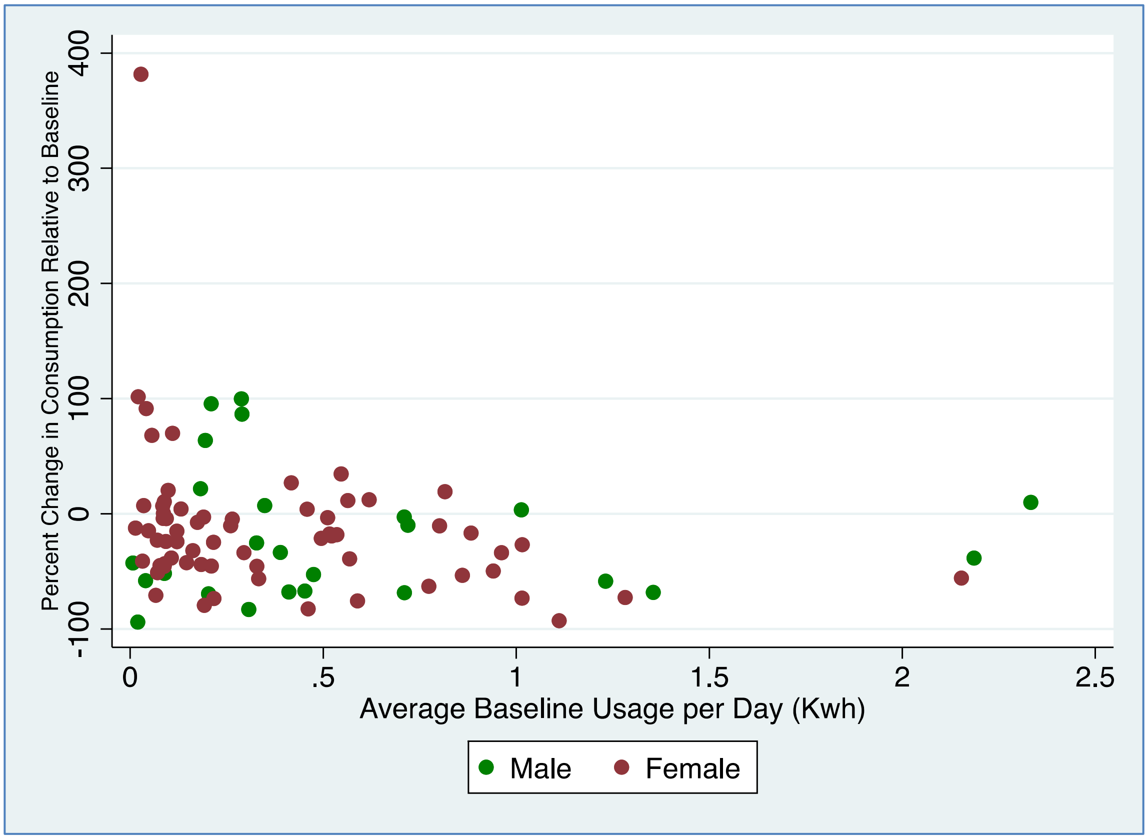


Figure 38:Energy Conservation Performance by Gender

Looking at the same factors examined in Equation 4, Table 23 shows the pre and post treatment interaction effects.

Table 23:Clustered, Pooled-Regression Results of Pre-Post Treatment Period Across Factor Variables

	(1) kwh_daily
1.gender_dum#~male	-0.311
	(0.450)
1.post_treat#~female	-0.537
	(0.397)
1.acad_yr#~freshman	0.212***
	(0.067)
1.post_treat#~sophomore	0.093
	(0.136)
1.post_treat#~junior	0.433**
	(0.176)
1o.post_treat~senior	
1.race#~White	0.020
	(0.100)
1.post_treat#~Black or African American	-0.305
	(0.193)
1.post_treat#~Asian	-0.039
	(0.113)
1o.post_treat~Two or more races	
1.assist#~No	-0.077
	(0.083)
1o.post_treat~Yes	
1.lasthouse#~1	0.121
	(0.100)
1.post_treat#~2 or 3	0.099
	(0.069)
1.post_treat#~4 or 5	0.097
	(0.092)
1o.post_treat~>5	
1.dorm_size#~single	-0.132
	(0.190)
1.post_treat#~double	-0.108
	(0.156)
1o.post_treat~three or more	
1.share#~no	0.083
	(0.100)
1.post_treat#~yes	0.091
	(0.114)
1o.post_treat~don't know	
1.estownuse#~much less	-0.513**
	(0.202)
1.post_treat#~a little less	-0.142
	(0.162)
1.post_treat#~about average	-0.267*
	(0.145)
1.post_treat#~a little more	0.163
	(0.322)
1o.post_treat~much more	
1.estownknow#~a little less	0.163
	(0.152)
1.post_treat#~about average	0.010
	(0.116)
1.post_treat#~a little more	-0.032
	(0.123)
1o.post_treat~much more	
1.devices#~1	-0.028
	(0.168)
1.post_treat#~2	0.074
	(0.139)
1o.post_treat~3	
_cons	0.718***
	(0.213)
Obs.	7094
R-squared	0.305

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Performance Comparisons across selected Survey Questions

Usage Feedback and Monitoring

As discussed in the Usage Feedback and Social Comparison section of this research, we can be confident that the existence of feedback has an effect on behavior, even if only for the short term. This research contributes some new information regarding frequency of usage feedback and performance. Most usage feedback programs push information to users, through reports and social media reminders. While some utilities do allow users to log into a web portal and view their usage, the barrier to feedback is still rather high.

However, the smart device-enabled GOEFER app is a pull device that allows users to check usage virtually anywhere and at any time. Based on the results of the post-survey question "How often did you check the GOEFER app to monitor your usage" (Figure 39), Equation 9 examines whether frequency of GOEFER app usage influenced behavior. Since no students indicated they checked the app hourly, it was not included in the OLS model.

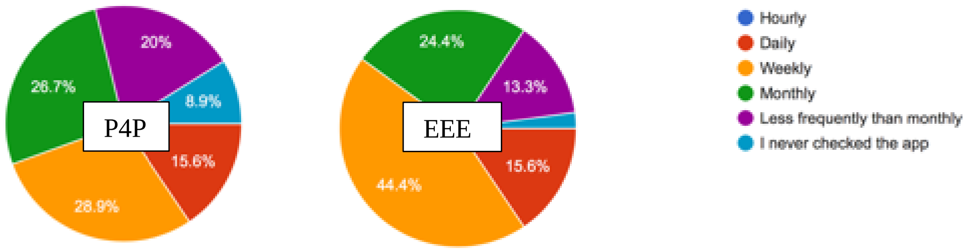


Figure 39: How often did you check the GOEFER app to monitor your usage?

Equation 9: Clustered OLS Model for comparing pre-post energy usage with GOEFER App usage

$$Daily\ Avg.Usage_{it} = \beta_0 + \beta_1 post\_treat_{it} + \beta_2 useapp_{it} + \beta_3 post\_treat_{it} * i.useapp_{it} + \varepsilon_{it}$$

Table 24 shows that those who checked their app daily conserved more energy relative to their baseline than those that checked weekly or monthly but conserved less than those who checked less frequently or never. However, none of the interaction results were statistically significant.

Table 24: OLS model results for Equation 9

	(1) kwh_daily
1.post_treat	-0.140**
	(0.062)
1b.daily	
2.weekly	0.145
	(0.132)
3.monthly	0.024
	(0.107)
4.less than monthly	0.018
	(0.178)
5.never	0.215
	(0.207)
1o.post_treat~daily	
1.post_treat#~weekly	0.026
	(0.076)
1.post_treat#~monthly	0.086
	(0.070)
1.post_treat#~less than monthly	-0.030
	(0.118)
1.post_treat#~never	-0.203
	(0.212)
_cons	0.359***
	(0.090)
Obs.	7094
R-squared	0.040

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Usage Migration

Because students had some power loads that were migratory, such as laptops and cellphones (fixed loads were required to remain in a GOEFER power strip) the post-survey asked students “when you consciously reduced your energy consumption in your room, how often did you simply use the same power in a different location?” (Figure 40).

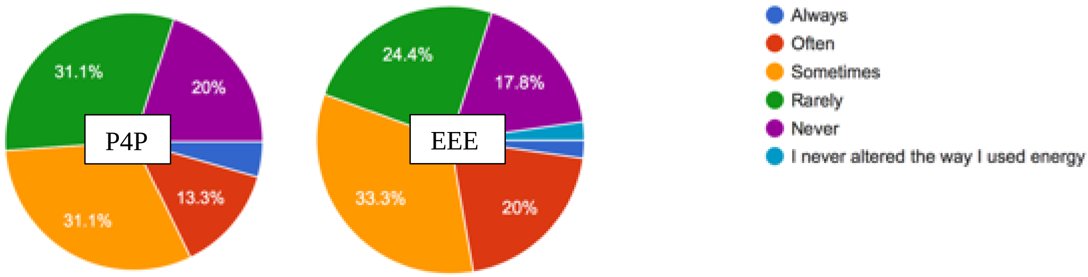


Figure 40: When you Consciously Reduced Your Energy Consumption in Your Room, How Often Did You Simply Use the Same Power in a Different Location?

This gives some assessment if energy migration might account for some of the measured reductions. In other words, how much did migration affect their usage behavior as well as measured energy usage? Equation 10 is the OLS model used to determine this effect.

Equation 10: Clustered OLS Model for comparing pre-post energy usage with student estimated energy migration

$$Daily\ Avg.Usage_{it} = \beta_0 + \beta_1 post\_treat_{it} + \beta_2 i.migrate_{it} + \beta_3 post\_treat_{it} * i.migrate_{it} + \varepsilon_{it}$$

Table 25: OLS model results for Equation 10

	(1) kwh_daily
0b.post_treat~e never	
0b.post_treat~e rarely	0.037
	(0.090)
0b.post_treat~e sometimes	0.314**
	(0.133)
0b.post_treat~e often	0.163
	(0.132)
0b.post_treat~e always	0.094
	(0.187)
0b.post_treat~e never altered	0.590***
	(0.063)
1.post_treat#~e never	-0.072
	(0.044)
1.post_treat#~e rarely	-0.086
	(0.074)
1.post_treat#~e sometimes	0.193
	(0.117)
1.post_treat#~e often	-0.029
	(0.086)
1.post_treat#~e always	-0.066
	(0.111)
1.post_treat#~e never altered	0.458***
	(0.063)
_cons	0.285***
	(0.063)
Obs.	7094
R-squared	0.094

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

The post treatment results of Table 25 suggest no discernible effect between the different survey responses. Those responding “never”, “rarely”, and “often” had similar levels of usage reduction, while those responding “sometimes” actually increased usage. None of those four were statistically significant. The only significant result was from a single respondent who responded, “I never altered the way I used energy”, who increased energy usage throughout the treatment period.

Thus, assuming students answered the survey question honestly, and understanding that each student may have a different estimate of words such as “often” or “sometimes”, there does not appear to be a correlation between energy behavior and levels of reported energy migration.

Financial Incentive

Although the financial incentive was clearly a factor in reducing consumption, its relative importance in behavioral change is uncertain. In response to the question “How significant was the financial incentive in changing your energy use?” (Figure 41)

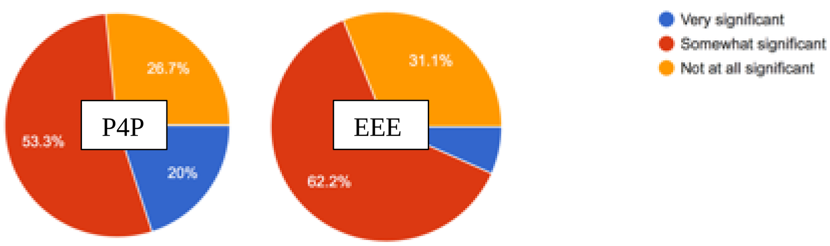


Figure 41: How Significant was the Financial Incentive in Changing your Energy Use?

Table 26 shows that across both groups 28.9 percent stated that the financial incentive was “not at all significant” in reducing energy use, while only 13.3 percent stated that it was “very significant”. For the majority of the sampled population (57.8 percent), the financial incentive appears to be part of several factors involved in changing behavior.

Table 26: Survey Responses to Importance of Financial Incentive

significant financial incentive	Group: Control	Treatment	Total
Not at all significant	12	14	26
	26.67	31.11	28.89
Somewhat significant	24	28	52
	53.33	62.22	57.78
Very significant	9	3	12
	20.00	6.67	13.33
Total	45	45	90
	100.00	100.00	100.00

First row has *frequencies* and second row has *column percentages*

Equation 11 models how this survey question correlated with outcomes.

Equation 11: Clustered OLS Model for comparing pre-post energy usage with importance of financial incentive

$$Daily\ Avg.Usage_{it} = \beta_0 + \beta_1 post_{treat_{it}} + \beta_2 i.importfin_{it} + \beta_3 post_{treat_{it}} * i.importfin_{it} + \varepsilon_{it}$$

Table 27: OLS model results for Equation 5

kwh_daily	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
1.post_treat	-0.113	0.056	-2.00	0.048	-0.225	-0.001	**
1.Not Significant	.	.	.	.	.	.	
2.Somewhat significant	0.002	0.109	0.02	0.986	-0.214	0.218	
3.Very significant	0.343	0.194	1.77	0.080	-0.042	0.729	*
1.post_treat#Somewhat significant	0.047	0.063	0.74	0.458	-0.078	0.173	
1.post_treat#Very significant	-0.300	0.116	-2.58	0.012	-0.531	-0.069	**
Constant	0.386	0.093	4.17	0.000	0.202	0.570	***

Mean dependent var	0.354	SD dependent var	0.478
R-squared	0.039	Number of obs	7094.000
F-test	5.874	Prob > F	0.000
Akaike crit. (AIC)	9387.822	Bayesian crit. (BIC)	9429.024

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 27 shows two important findings, 1) students who thought the financial incentive was "very significant" in changing their energy use reduced their average daily use significantly, and 2) those students had significantly higher levels of baseline use than others. Again, this reinforces the importance of how higher potential gains effectively motivated students to change behavior, both in their stated *and* revealed preferences.

There are several theories of behavior that are consistent with this result as discussed in

Theories of Behavior applied to Energy Consumption. First, it is well established that simple usage awareness will reduce consumption. The majority of studies that examined increased awareness in households must still acknowledge that reduced consumption is at least partially incentivized by lower energy bills.

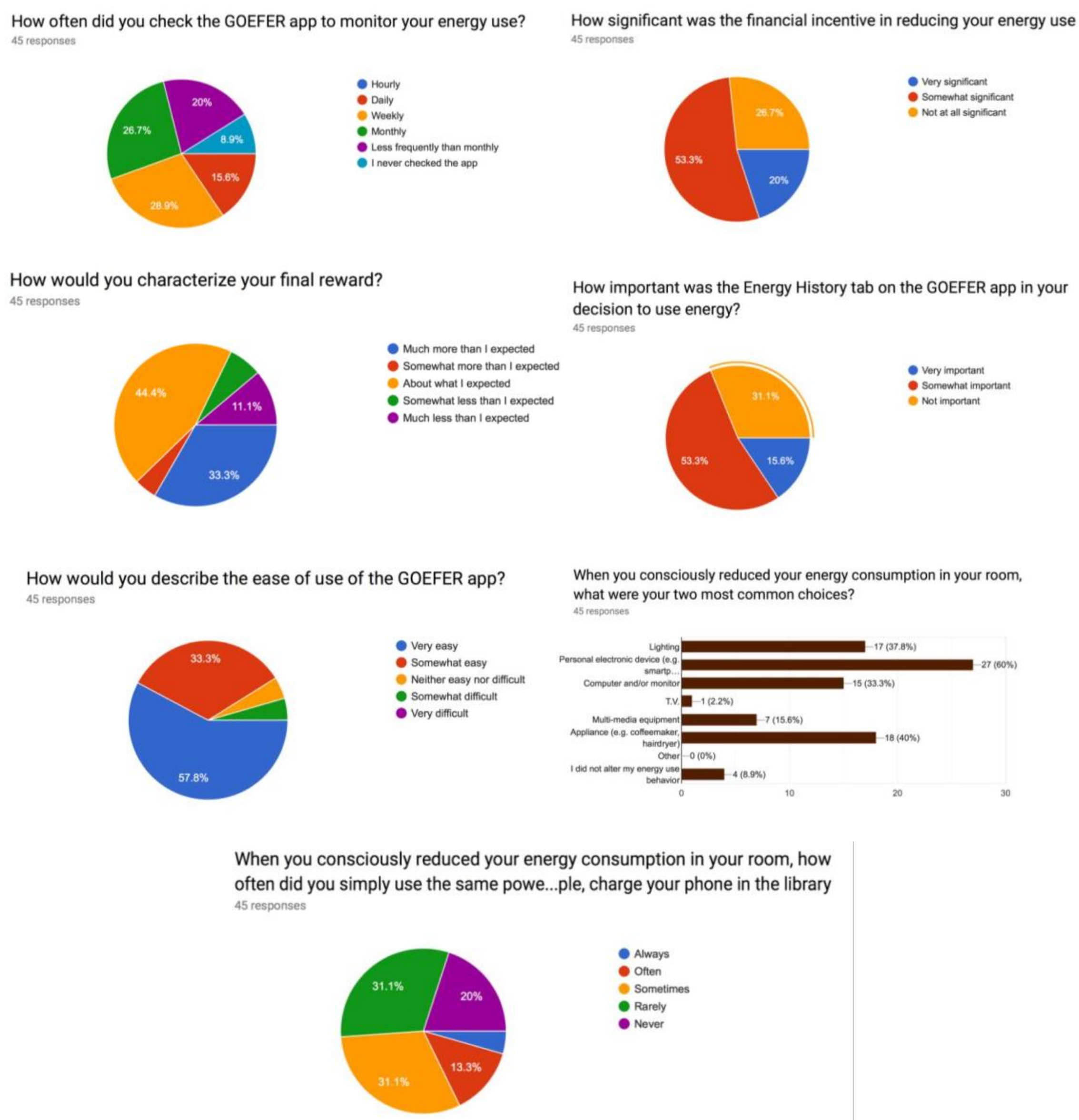


Figure 42: Post Experiment Survey Results (P4P)

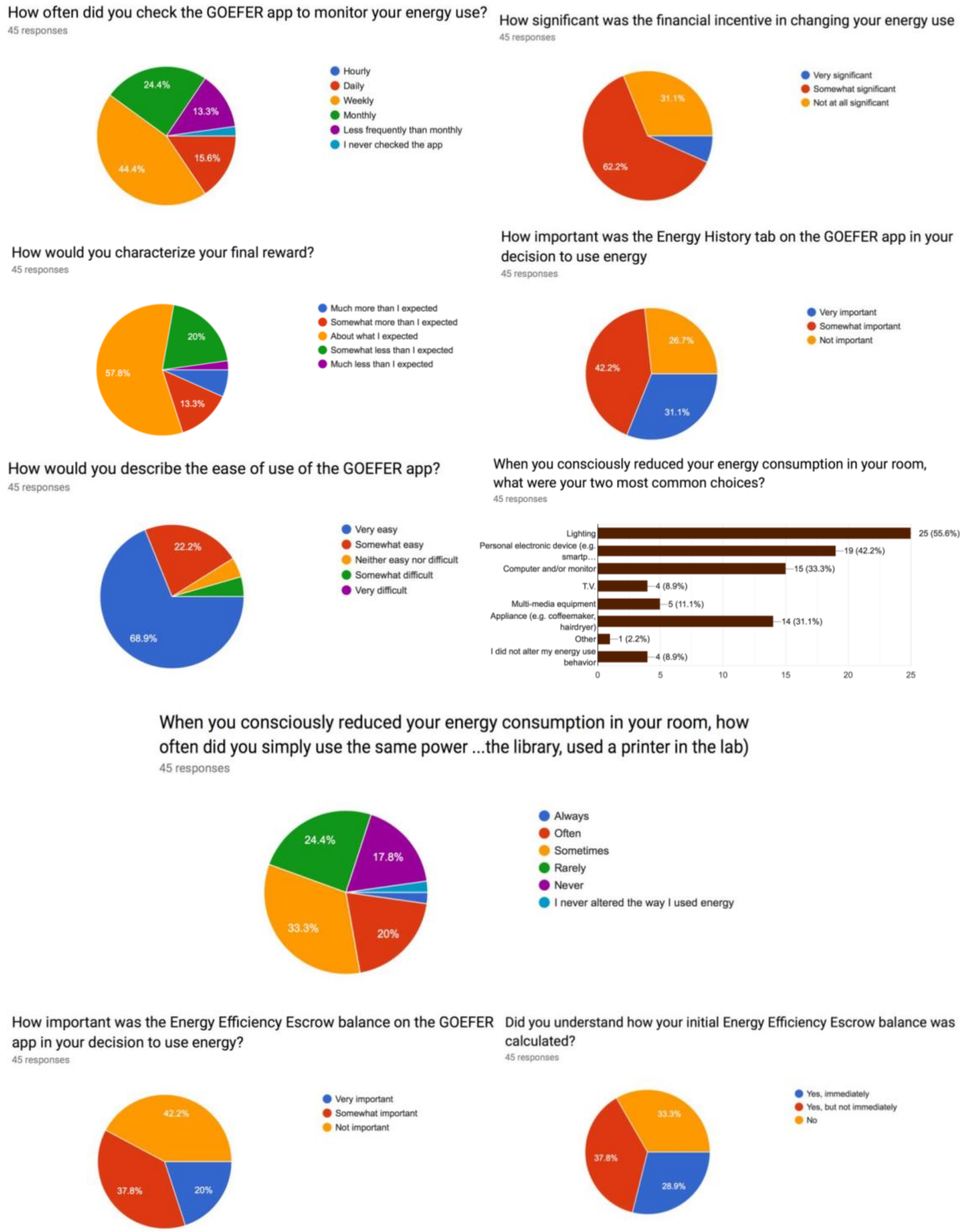


Figure 43: Post Experiment Survey Results (EEE)

CONCLUSIONS AND POLICY IMPLICATIONS

The conclusions of this project should be regarded as preliminary with limited external validity. The research design intentionally simplified many of the parameters to reflect the fact that the research applications of prospect theory, and loss aversion, to demand side management (DSM) is sparse. Still, this research is novel and establishes a new framework for interested utilities to design a pilot program that can leverage a larger sample size and a more heterogenous population.

Achieving energy reductions approaching those found in this research are unlikely due to several factors, 1) the flexibility of adjusting plug-level loads is likely much higher than for other household loads, such as space/heating cooling and hot water heating, 2) individuals endogenously select into any experiment and are not truly a random population sample, thus some self-selection bias and/or Hawthorne effect may exist, and 3) the amount of energy migration could not be precisely measured. This latter observation may be endemic with any residential household study to some degree.

Consumers respond to financial incentives

This research does support the neoclassic economic tenet that individuals respond to incentives. This is significant for several reasons: 1) Pay-for-performance (P4P) programs are still almost non-existent in the U.S. residential energy sector. There are currently no publicly available empirical results from which to compare the results of this research, 2) technology, such as the GOEFER app and smart meters, is becoming increasingly ubiquitous and affordable, allowing for creative ways to explore more complex ways of engaging with consumers.

Financial incentives are effective in DR programs as well, using a wide range of framework mechanisms, including dynamic rate structures. Having options to direct demand management over a wider timeframe and/or to targeted service area locations will likely become more economical as the electricity grid shifts to more renewables and storage. P4P/EEE type programs coupled with dynamic usage feedback offer curtailment and, very likely, energy efficiency behavioral modifications. Unlike today's DR programs there is no need to predict when incentive periods are being offered and, thus, requires less attention by the consumers. In fact, DR programs do not require consumers to stay engaged with their household usage except for very few times a year. Despite some of the similar financial frameworks, DR programs show little evidence of energy efficiency behavior, but rather curtailment behavior that shifts usage patterns. HERs and energy audits appear to the be only widescale, non-rebate programs with empirical evidence showing energy efficiency gains. Unfortunately, neither use rate-based financial incentives to reduce energy use.

Although it is clear to anyone familiar with electricity rates that the incentive rate to conserve a unit of energy was spectacularly high for this experiment[34], the research results should not be readily dismissed as impractical. Although it was not explicitly

[34] $1 kWh is considerably higher than the average U.S. residential electricity rate of $0.128 kWh in March 2019 (according to EIA). Accordingly, this rate would not be economically efficient.

asked on the survey, persons of this age typically do not have a history of paying energy bills and, thus, are unlikely to know that the incentive was favorable to them relative to industry standards. The incentive amount was structured to ensure the participants had a potential reward that would reasonably cause them to be attentive to both the amount and their energy use.

Although not the primary objective of this research, this is one of the first studies to quantify how effective a real-time usage feedback program might actually perform in concert with a rate-based financial incentive. Paying consumers directly to use less energy using only their historic and current usage information avoids some of the costly engineering estimates required of current P4P programs. This research found that an *effective* savings of 24.2 percent could be achieved for the unit rate. Other factors would need to be considered in scaling this research for a wider set of households. For instance, are high relative incentive rates needed to achieve the program's desired outcomes, in view of the induced penalties of non-responders, or can lower rates achieve the same results?

An added financial incentive that was not integrated into this research is the fact that using less energy results in a lower energy bill. As discussed earlier, some of the residential household charges are demand charges and do not change significantly based on usage. However, consumption charges would reduce user costs even beyond the rates offered by P4P-type programs. Conveying to a customer their combined savings (consumption charge reductions plus P4P/EEE savings) would be is yet another opportunity to change behavior in real-time, using usage feedback.

Importance of Understandable Framework Details

The results of the EEE subgroups in Research Question #2 of the previous chapter make it clear that program information that is shared with the customer needs to be well understood. In this research, those students who did not understand how the EEE balance was calculated were largely deterred from reducing their consumption relative to all other groups, including other EEE subgroups. Despite having other tools available to gauge performance, this subgroup had trouble reconciling their usage with a single program element they did not understand.

In developing future smart device programs and apps, ensuring customer understanding of all features should be prioritized less they become a distraction. In this study a premium was not placed on ensuring consumers understood all app features before they were deployed. This was partly by design to minimize any bias. It was assumed that consumers would most likely reconcile how their EEE corresponded to their usage. It shows that features aimed to overcome bounded rationality and cognitive barriers can actually inhibit behavioral change if not fully understood by the consumer.

Matching Energy History with Proper Incentives

The finding that those with higher average baselines tended to have higher relative levels of energy reductions does have policy implications. Although the overall efficacy of a P4P/EEE-inspired program may be expected to be greater per-program-dollar, a service area targeted toward heavy energy users might create equity concerns. With low income users, the number of discretionary loads are likely more limited, leaving a larger percentage of program funds directed toward the more affluent. Many of these arguments are similar to those made against dynamic pricing of DR programs.

One alternative would be to alter the rate structure to be more favorable toward lower income users, so as to balance the reward structure. Other types of energy efficiency incentives may also be more appropriate for low income users, such as weatherization and subsidies for energy efficient durables. Targeting subsidies toward low income users would also reduce the free ridership problems inherent with users that have time to overcome information asymmetries and have easier access to credit.

According to the Energy Information Administration (EIA) residences account for 37 percent of all electricity sales in a $380 billion U.S. market. Even marginal shifts in conservation can have tremendous economic benefits. Also, major segments of the economy, such as college campuses, charge flat fees for energy usage regardless of actual usage. Although there are sound economic reasons for doing so, it does limit their ability to incentivize conservation.

As the costs of administering these types of experimental programs are weighed against the benefits, they should be compared with supply-side incentives, such as cost-of-service regulation. They should also be compared with other DSM programs, such as energy efficiency rebates, dynamic pricing, and other incentives. The costs and benefits of these “nudges” will be used to help inform regulators as to how new demand-side technologies might enable more cost-effective alternatives to supply side measures.

Recommendations for further research

This research provided a very limited framework for how prospect theory could be applied to incentivize energy conservation, a continuously decrementing balance on a smart app to a large group of college students. Obviously, applying this to actual residential households would greatly improve validity. Other interesting variations are mentioned below.

- Quantizing rewards could change how consumers view losses. What if potential rewards were presented in increments? For instance, an EEE could reflect a tiered level of payment based on the magnitude of the savings. One NRDC report that surveyed historic P4P programs showed that tiered incentive payments are critical to achieving large conservation targets because, otherwise, there is a tendency for consumers to only address “low-hanging fruit” (NRDC, 2017).
- Research shows that non-pecuniary incentives that activate social norms have worked effectively at-scale in residential household environments. Loss aversion could effectively be used in this context by urging consumers to maintain a certain status. For instance, to maintain “platinum” saver status a consumer would have to demonstrate savings over a fixed period of time. The incentive would be to avoid dropping to “gold” or “silver” status. These could be used as injunctive norms and/or shared with those who opt-in to a program.

- Feelings of affect were not explicitly measured in this experiment, although no participant decided to opt-out of the program. Overall satisfaction of a program must be reconciled with outcomes. For instance, one study showed positive outcomes (over a financial incentive) by giving children a token for achieving good grades. Tokens were taken from students whose performance degraded. (Cullen, Levitt, Robertson, & Sadoff, 2013) Obviously, this brings up other policy considerations including social costs and possible moral hazards.
- This experiment reflected curtailment behavior much more than energy efficiency. Also, no information was provided to students about how they could reduce consumption. A more comprehensive EEE program could address both. Removing information asymmetries with targeted messages could further reduce consumption. For instance, consumers might see "replacing three incandescent bulbs with LEDs will, on average, add $10 to your EEE balance over one year" or "upgrading to an ENERGYStar dishwasher can add up to $138 to your EEE balance over three years" as a way of directing specific types of activities.
- Given that revealed discount rates for durable goods have differences among sociodemographic factors, such as education and ethnicity, the benefits of an EEE may favor those groups with higher revealed discount rates. This experiment essentially represented a homogenous education level.

- Loss aversion tends to have geographic and cultural variation.
- This research was essentially a one-shot experiment. It is unclear how both control and treatment groups would react given a new incentive period. It is realistic to hypothesize that as the control group (P4P) became more confident in predicting their gains, whereby they are "less surprised", that consumption may gradually increase in a multi-shot experiment. There are plenty of examples whereby consumption increases after the initial exposure. For instance, Home Energy Reports (HERs) tend to have the largest energy consumption reductions early in a performance or treatment period, tapering off as the frequency of reports increase (Allcott, 2011; Ayres et al., 2013).
- Comparing program costs of rebates and subsidies with a P4P/EEE-type program would help determine how to structure a portfolio of options. It is unlikely that a one-size-fits-all approach is the most effective. Even combining the two in some fashion provides some interesting options. For instance, what if part of a EEE could be used to help purchase, or subsidize, a more energy-efficient durable product?
- With low-income households often most in need of energy savings, creative programs whereby high-income users could effectively save on behalf of lower income users. Sustained savings could be directed to energy efficiency projects for low-income households. Similar human resources (HR) policies allow for donating leave days to those in need.

Practical Applications

The electricity utility sector is undergoing rapid change, brought about by new technology, declining demand, environmental imperatives, and customer preferences. Regulators continue to struggle to find ways to incentivize utilities to reduce demand. This is understandable for many reasons. However, energy conservation, either through energy efficiency or curtailment, continues to be among the most cost-effective ways of structuring a socially optimal energy sector, where the greatest output of goods and services can be obtained with the least amount of primary energy.

P4P programs, which are just beginning to evolve in the U.S. residential sector, should continue to draw on behavioral economics to help inform how energy efficiency incentives are framed. As more customers become accustomed to using technology, such as smart phone apps, to reduce information asymmetries opportunities abound in pairing behavior with incentives. The EEE, or derivation thereof, is just one framework that behavioral economics can play an important role.

How an EEE would be employed by a utility company must address several challenges not of concern is this early research. First, can reduced consumption be sustainable? After all, the primary value and economic justification for a P4P-type program is to permanently reduce the incentivized load and, thus, lower the overall demand footprint in a given area. An efficient program would attempt to minimize rewarding behavior that may simply be reverting to the mean. Other control factors not used in this research, such as heating/cooling day offsets, would likely be necessary. Establishing a reasonable baseline period would require some attention, perhaps a multiyear sampling period. Also, changing the length of the incentive period of performance may show some variation. For instance, if beginning EEE balances were larger it might incent consumers to make larger investments in energy efficiency upgrades. Also, a longer period of performance may help normalize year-to-year variations that mask sustainable reductions.

Obviously the EEE-P4P program examined in this experiment does not suffer from the constraints of seasonal variability. Since this program looked only at plug-level loads that do not tend to vary with weather and other factors, the continual comparison of daily, weekly, and monthly usage makes usage comparison seasonally agnostic. A program that incorporated full household usage would need to factor in seasonal variations. For instance, monthly comparisons from the previous year would likely make more sense given that space heating/cooling is the predominant energy load. A variable rate incentive that reflected the variability in wholesale rates throughout the year could also be explored. Obviously, the cost of the energy efficiency incentive would have to be factored into the rate base approved by regulators, and likely paid for by other consumers. Although this may seem counterintuitive it makes sense from a social economics perspective. Remember that the EEE-P4P incentive cost has virtually no capital recovery costs embedded, only the costs of setting up the feedback usage framework, which would have virtually zero marginal costs if the program is expanded.

Escrows could also be used in conjunction with other behavioral and informational tools. For instance, escrows could be paired with a utility marketplace, whereby balances can be applied to offset the purchase of energy efficient durable goods, smart devices, or home audits. They could be used to run competitions and reinforce personal commitments for energy use reductions.

EEE-P4P programs also address a growing concern among some energy policymakers; that of rebound effects. While it remains uncertain to what extent consumers are choosing to use the savings from energy efficiency rebates and subsidies on other energy-generating sources, programs that reward households and consumers for *absolute* reductions would be more effective as a long-term demand side management (DSM) tool. Updating a household's average baseline is one way of normalizing the incentive. In other words, as household energy use decreases, the incentive would naturally decrease as well, reflecting a lower overall average. In this way, the EEE framework used in this research maintains a higher incentive for households that do not make usage change, which makes for a more equitable and effective policy.

An EEE could also help overcome status quo bias by making it an opt-out program. The cost of adding an additional customer is extremely small. Customers may view their balances as an "energy efficiency dividend" much as they would a tax rebate.

The goal for energy utility regulators should be to incentivize reducing overall demand if it is less expensive than to add generation. This makes the value of these DSM programs much more comparable to supply-side options; "is the unit cost of removing 1 kWh of energy off the service area baseline cheaper than adding 1 kWh of generation?" remains the important question. Additionally, regulators should try to minimize any negative effects of behavioral programs. Although some worry that prepay electricity programs may potentially negatively affect vulnerable populations, the EEE framework does not suffer from that problem.

APPENDIX A

During the 2018-2019 academic year, Dickinson College Residence Life and Housing is supporting a research project being conducted by George Mason University and Dickinson College faculty and students on energy usage. Your room, along with others in your residence hall, has been identified as a candidate location for the project. A small financial compensation by the researchers has been set aside for you if you decide to participate, which is completely optional. Please read the attached consent form for more details. If you wish to participate, please sign the consent form and return it to me electronically or drop it by the Residence Life and Housing Office (lower level of the Hub) no later than October 5, 2018.

APPENDIX B

4539 Metropolitan Court
Frederick, MD 21704
info@GOEFER.com
204-457-9667

GOEFER®

GOEFER-strip

Dimensions (L x W x H)	12.76” x 2.46” x 146”
Weight	26.45 oz.
Installation	Floor, Desktop or Wall Mount
Operating Temperature/ Humidity	32°F ~104°F 10%~90% (non-condensing)
Storage Temperature/ Humidity	-50°F~158°F 5%-90% RH (con-condensing)
Warranty	1 year
Certification	FCC ID: 2AN37SOW014, UL: E496833
Environmental Directive	Compatible with WEEE, RoHS
Operation	
AC Plug	Rating: 15A 125V, Plug: NEMA 5-15P, Cable length 4ft
AC Outlet	Rating: 15A 125V Receptacle: NEMA 5-15R, UL498 5-15R, Quantity: 6pcs
Circuit Breaker/ Power Switch	Power over current protection, manual reset, manual turn the unit power on/ off
DC Output	5v/ 3.1A (3 ports total), USB for charging only
Touch Switches	Touch the 1-6 to turn outlet power on/ of
LED Indicator	1-6, Power, Wi-Fi, Protected, NOT Grounded

DISCOVERING VALUE BY ANALYZING THE ENERGY YOUR ELECTRONICS USE EVERYDAY

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Joel Hicks is a former U.S. Naval Officer who served in the nuclear submarine community as well as completing multiple assignments in DoD space acquisition and operational communities. He obtained his Nuclear Engineer credentials through Naval Reactors, and his last active duty assignment was as Deputy Director, Joint Space Operations Center (JSpOC), Vandenberg AFB, CA. Mr. Hicks has also taught two graduate courses, *International Issues in Energy Policy* and *Science, Technology, and Energy Policy* at The George Washington University's Elliott School of International Affairs (ESIA). Currently, he is an adjunct professor at George Mason University (GMU) teaching *Public Policy Analysis* and *Governance and Energy Policy*. He frequently writes about demand side management (DSM) of energy systems with a focus on energy efficiency, behavioral economics, and public sector energy governance/institutions. He is a student fellow at the Center for Energy Science and Policy (CESP).