Knowing Where the Power is Going:

New Opportunities for Household Disaggregated Electrical Usage Feedback

A thesis submitted by

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ABSTRACT

US households have significant potential for smarter use of electricity, but behavioral changes for more efficient utility use may be hindered by households' lack of information about their appliance-level, disaggregated usage. Earlier studies in household electricity usage have been hindered by technological constraints, and robust findings about the relative effects of various feedback methods have remained elusive. Recent innovations provide methods for testing consumer responses to disaggregated electricity usage (DEU) feedback that are both more reliable and potentially scalable to wider populations. Despite the emergence of these new technologies, study design issues persist, and reliable estimates of the absolute and relative effects of various feedback methods remain have not yet been attained. This paper provides an overview of the new opportunities in DEU feedback research, examines findings and limitations of previous work in the field, and proposes a controlled study to evaluate relative usage impacts of electricity feedback treatments.

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PREFACE: A WORLD WITHOUT PRICES

Imagine grocery shopping in a society where there were no prices listed on retail goods. Imagine further that in this world, families received a single bill for their grocery purchases at the end of each month, and that many families naturally opted to pay this bill via automatic withdrawal from their bank account.

In this world, customers would not be able to make sound economic decisions around their food purchases. Perhaps there would be resources and websites offering consumers a general idea of the seasonal cost of fruits and vegetables. Customers could try to inform their purchasing by checking financial markets to for the price of commodities such as milk and wheat. Shoppers might have a sense that the tomatoes and fresh corn that arrive in droves in the summer are relatively cheap, and they could perhaps make some vague connections between certain purchases and various spikes or dips in their monthly grocery bill.

But otherwise, consumers would be in the dark about the costs of their purchasing choices. Only the most astute shoppers would know of the savings from purchasing seasonal items and limiting their purchases of beef, lobster and imported cheeses. Without considerable research, consumers would not be aware of the range of costs of different brands of orange juice, or the advantages of purchasing milk by the gallon rather than by the pint. They would not know when chicken or strawberries were on sale, perhaps available at a fraction of their regular cost.

With no ability for supermarkets to advertise sale items, and consumers unable to respond to these temporary discounts on oversupplied goods, the amount of waste in our food system would likely be greater. Households would spend more on their groceries, while enduring lower quantity, quality and diversity in the household diet. Stores, likewise, would sell less while charging more. Facing this consumer market, our agricultural system would be less efficient, less profitable and less productive.

Some wealthy households would pay little attention to cost because grocery shopping would still a small share of their household costs. Other families would become grocery price "enthusiasts", doing research to speculate on food prices and comparing their monthly bills to their grocery inventories to gain insights into the costs of their purchases.

The circumstances would be worse for poorer households. Some of these families might consume less food, and limit the range of food items they purchase. Awareness campaigns might educate them to shift to canned, frozen or processed foods that are generally less expensive and more stable in price, and might recommend specific economical foods, perhaps even offering incentives for families to purchase them. But most families would face the undue burden of high and fluctuating food costs. Grocery shoppers in this world would be unable to make optimizing decisions based on their preferences and budgets – they would thus be unable to avoid a lot of bad choices.

When it comes to home energy use, most Americans live in an inefficient economic world. We wake up and take a long, hot shower, turn on the television, boil water for our morning coffee, run the dishwasher and leave the house with the thermostat set on high. We run the dryer for an hour for a few clothing items and keep air conditioning on with the windows open. Many of us have a general sense of the costs of electricity, that we should turn lights off and be aware of limiting our cooling and heating. But even many well-informed households have a tenuous connection to the actual dollar costs of our utility use. In the home, most of us are not given the informational tools to become efficient, informed consumers.

CHAPTER 1: INTRODUCTION

This paper will attempt to answer the following motivating questions:

1. Why are studies about multi-level electricity use feedback important from an environmental and planning perspective? How does feedback fit in to efforts to change household usage patterns in a way that results in more economical use?
2. What is the best evidence of the potential for Disaggregated Electricity Usage (DEU) feedback in households to positively influence consumer usage patterns?
3. What gaps in our knowledge exist with respect to consumer response to utility usage feedback, and how should future research address these gaps?
4. How might we design a study in today's socio-technological world, in order to better address these questions, accounting for earlier limitations in research design?

Consumers generally exhibit a limited understanding of their energy bills, and have a low awareness of electrical use and costs in general (Southwell *et al.* 2012, 7; Sundramoorthy *et al.* 2011, 23; Bartram 2015, 52). Furthermore, consumers generally lack the tools to and information to understand whether they are using electricity efficiently, and how to gain efficiency (Gardner and Stern 2008, 14). A convoluted monthly bill in arcane units such as “kWh,” “joules” or “therms” is the only tool available for most consumers to evaluate their energy consumption.

Thus, a typical household’s lack of understanding of their actual usage and its costs at the appliance level leads households to become sub-optimal users of their electricity. We know that heat, hot water and electrical appliances use energy, and some of us have a general sense of total costs through our bills, but most consumers’ connection to energy use is tenuous. And to date, researchers do not have clear evidence of the degree to which the disconnect between electricity usage and its costs brings about waste.

Actual usage of electricity within the home occurs dozens of times per day in ways both large and small. If we want to influence consumers to be more responsible and economical with their energy use, presenting usage to households in indecipherable units just a few times per year is a grossly inadequate form of information, and generates little feedback. There is evidence that even the sporadic visibility of electrical costs significantly impacts usage patterns when compared to no visibility at all: over 1/3 of American homes pay their electricity bill via direct withdrawal from their account, and a

2015 study found that households who pay their electricity bill via Automatic Bill Pay (ABP) use 4-6% more electricity than those who pay their bill manually (Sexton 2015, 230). This study controlled for various determinant factors of electricity use, including home size, household income and family size. Additionally, the study found that ABP resulted in a higher increase in usage among lower income households than higher income households.

But why attempt to reduce household electricity use in the first place? Changes in household behavior around energy use have a substantial potential to reduce overall electricity use and control the human impact on climate change (Boudet, Flora, and Armel 2016, 445). Energy use is a primary contributor to climate change, with the majority of greenhouse gases emitted as a by-product of energy production. Buildings account for over 1/3 of all energy use, with residential buildings accounting for over half of that total (US EIA 2017, 29). Buildings also account for nearly 3/4 of total US electricity use (US EPA 2017). There is also a public interest in changing usage *patterns* as well as overall usage, since both production cost and relative emissions of electricity per unit varies according to overall usage. During "peak demand" times such as hot summer afternoons, electricity is more expensive to produce and often more emissions-intensive, due to the nature of generation sources that can be quickly and briefly turned on (Torriti *et al*. 2015, 892). From a household economic standpoint, with few exceptions, electricity prices have been rising steadily in the US, and overall electricity demand is expected to increase steadily (Bernstein and Collins 2014, 219).

There are a range of interventions that are currently available for use in homes to increase household awareness of electrical use. Simple technologies and smart-metering technology can offer households more detailed usage information, either in real-time, or in hourly or daily intervals. Electricity providers have sought various methods of enhanced billing and other awareness campaigns either to inform households of changes in their consumption, or to compare their usage with neighbors' usage. Some of these interventions have shown real results in reducing electricity usage in the range of 2-3% (Lossin, Loder, and Staake 2016, 151; Allcott 2011, 1082–83). However, these methods have not achieved a granular awareness among household residents of *where the power is going* – how much each appliance is using, and how much that use costs.

What if consumers were exposed to the cost of their electrical use itemized by appliance, and provided in real time? What if this itemized electrical use, known as *disaggregated electricity usage* could be compiled and presented in a regular, real, and understandable way, so that families would at last understand the true cost of their various electrical uses, and as with other purchasing decisions, could be empowered to adjust their use according to their preferences?

There is some evidence to suggest that direct, personalized electrical use feedback may result in an average 4-15% reduction in home energy use (Fischer 2008, 87; Armel et al. 2013, 216), and that use of in-home displays (IHDs) can produce significant reductions in electricity use, and can enhance the effectiveness of dynamic pricing programs (Faruqui and Sergici 2010, 216; McKerracher and Torriti 2013, 388). But previous studies comparing DEU feedback to aggregate feedback offer a wide range of findings and conclusions. Among known studies, results range from a negligible effect on household usage, to reductions in household usage as high as 38% (Kelly and Knottenbelt 2016). These previous studies have been plagued by significant problems in analysis due to the small sample sizes of some studies (Armel et al. 2013, 215), a lack of publicly available datasets, and issues of unequal treatment groups (Kelly and Knottenbelt 2016). There is a great deal yet to be learned about how disaggregation may be a tool to reduce household electricity consumption.

With disaggregated energy use feedback generally, there appears to be a correlation between energy use reduction and both the level of detail and specificity of the feedback and amount of consumers' interaction with the monitoring technology (Armel et al. 2013, 220; Rowlands, Reid, and Parker 2015, 384). There is also promising evidence of the potential for substantial usage reductions (and thus cost savings) among a targeted group of energy users, as variations in energy use among apparently similar households can vary widely, by as much as 200-300% (Gram-Hanssen 2013, 451; Armel et al. 2013; Lutzenhiser 2014, 146; Murtagh, Gatersleben, and Uzzell 2014). Various disaggregation studies have also shown large variances in appliance level usage on a household-by-household basis: appliances in some homes used 12 to 50 times more electricity than equivalent appliances in other homes (Rowlands, Reid, and Parker 2015, 390). Even with an intervention as complex as DEU feedback, a focus on the highest-consuming households and the most energy-intensive appliances may represent low-hanging fruit.

Studies comparing various technological approaches to electricity use feedback, both aggregate and disaggregated, have produced mixed results regarding the advantages of more granular feedback (Kelly and Knottenbelt 2016). But studies of the *behavioral* dimension of household energy use has been given less emphasis than technological, economic, and policy based approaches (Armel et al. 2013, 216; Allen, Dietz, and McCright 2015, 134).

Researchers are largely ignoring a major subset of inquiry the field of utility use - that usage is in most cases a product of human decisions and behavior with respect to the end-products they get from their use: cool air, dry clothing, hot water, television, etc. (Fischer 2008, 80). Similarly, we are missing true comparisons of various types and levels of feedback that control for potential variations in treatment groups. Existing studies tend to evaluate a narrow range of feedback regimes, and/or feature serious bias concerns from design flaws or product limitations (Kelly and Knottenbelt 2016). Only very recently, accessible and scalable technologies have become available that will allow researchers to answer these questions, both for the purposes of knowledge about human consumption behavior, and to direct policymakers as to which types of interventions can lead to smarter household electricity use. (Faustine et al. 2017, 2).

A multi-level study, using a common feedback medium via in-home display, and differentiating to multiple sub-treatment groups can control for treatment group variations that have plagued previous studies. This inquiry will lead us toward real, replicable policy regimes, and can also work in concert with other areas of study around electricity consumption. While there are numerous case studies in consumer response to dynamic pricing structures, suggesting low to moderate price elasticity for electricity consumption, there is a direct relationship to the level and type of consumer feedback, and price elasticity curves are highly affected by the degree that consumers know the price of what they are consuming (Labandeira, Labeaga, and López-Otero 2012, 633; Faruqui and Sergici 2010, 201; Fan and Hyndman 2011, 3717; Boonekamp 2007, 153). Prior to the advent of better feedback methods, energy ratings and awareness methods were recommended to improve consumer response (Boonekamp 2007, 154).   Indeed, influencing consumer behavior towards optimal individual (and societal) consumption patterns may begin with improving our current structure of price awareness.

A study that tests a range of salience and detail of electricity feedback with a common medium across treatment groups also has implications over a range of household consumption behavior. While here we are examining electricity alone, the consumer experience with electricity is akin to most other home utility uses – we consume source fuels (electricity, natural gas, home heating fuel, etc.) to produce outputs (light, heat, refrigeration etc.) and pay for those source fuels in dollars.

Buying decisions outside the home depend on the levers of economic utility, price elasticity and salience: our optimal purchasing decisions result from our preferences and needs set against our purchasing power. But our *real* purchasing (or usage) decisions of electricity can be impacted heavily by our lack of information about price (Labandeira, Labeaga, and López-Otero 2012).

CHAPTER 2: MOTIVATION

A confluence of three major trends motivate our new general line of inquiry regarding the potential for technology to influence household energy use behavior.

1. **New policy initiatives are responding to energy management challenges**

With few exceptions, the price of electricity is rising in residential and commercial sectors (US EIA 2011, 252). As part of this rise in price, hourly and seasonal fluctuations in electricity demand have remained a challenge for electricity providers to manage. Most electrical providers charge flat rates, although the production cost of extra electricity during peak-demand times is considerably higher than steady base-load power (Asadinejad and Tomsovic 2017, 216). Sub-national governments in the US (which regulate electricity prices on behalf of their constituents) have begun to encourage electricity providers to take more innovative approaches to managing the grid through incentive initiatives and dynamic pricing structures (Asadinejad and Tomsovic 2017, 215). These market-based mechanisms allow electricity providers to change consumer usage and usage patterns, and by reducing the demand for expensive, peak-load electricity, they can reduce the overall cost of electricity to the public at large.

2. **The public is beginning to address climate change as an energy issue**

Climate change is primarily an energy problem; however, the dominant public discourse over the global challenge of climate change gives scant attention to the fact that global warming pollutants, including CO2, are almost entirely emitted as a byproduct of energy production and use (US EPA 2017). Thus, necessary societal responses to mitigate climate change are likely to come largely from a combination of cleaner energy production and smarter energy use. All levels of government in the United States are beginning to implement clean energy and efficiency policies, from a range of federal policies around electricity production and transportation implemented over the last decade, to state and regional renewable energy standards, to local cities and towns implementing building standards and incentives for renewable energy production. Governments at all levels are responding to the need to reduce greenhouse gas emissions, and these governments, along with the electricity providers they regulate, are seeking new opportunities for emissions-responsive electricity use among citizens.

3. **New technology is expanding the potential for disaggregation research**

While the previous two motivations are central to this method of inquiry, there are more recent technological developments that portend a dramatic change in our relationship with energy use. While utility use feedback, or eco-feedback, as it is described in academic circles (Bartram 2015; Buchanan, Russo, and

Anderson 2014; Allcott and Rogers 2014) is a decades-old area of inquiry with significant past research, recent technological innovation has made methods of data collection and eco-feedback in homes not only possible where it once was not, but also more feasible, in both cost and implementation. In recent years, data innovation has offered researchers greater capabilities in data analysis, and the hardware that performs the monitoring has become far less expensive. The type of electricity monitoring that involves a monitor attached to a single point of an existing home or business electrical system and monitors most or all electricity use at the appliance-level is called "Non-Intrusive Load Monitoring" (NILM) (Hart 1992). A monitoring and eco-feedback system that once may have cost several thousand dollars and required a complicated installation by technicians now may involve a NILM system that costs only a few hundred dollars and may not need to be installed by a trained technician (Jain, Taylor, and Culligan 2013, 409–10). This points to mitigation of complications of previous studies due to easier implementation, but it also suggests that larger and representative sample sizes are a realistic possibility for the first time (Rowlands, Reid, and Parker 2015, 391).

To investigate these potential improvements in eco-feedback, this paper will provide a basic background on previous work in disaggregation research, and present a review and summation of findings within existing literature. We will also present a framework for a study to examine some of the under-researched (or poorly researched) areas of consumer response to electricity use, based in part on the latest study design considerations that have come about through lessons learned in previous social research on consumer response to electrical usage information, and incorporating new or newly accessible and scalable technologies.

CHAPTER 3: BOUNDARIES OF INQUIRY

Investigation into DEU is motivated by the rapidly-changing landscape of more powerful and more readily scalable technological hardware, and by more accessible and accurate data collection and processing. These circumstances permit study design elements that were infeasible just a few years ago, and researchers may now be empowered to design studies that are more cost-effective to implement, less logistically challenging, and which reduce many (but not all) of the biases that have caused skepticism of and limited reliability in previous studies.

But just as this changing landscape presents an opportunity, its rapid evolution also limits our ability to make long-term assessments. Technology may continue to advance in this field, offering even more efficient, cheaper and more comprehensive study structures than we have today.

As important as it is to identify what this paper will thoroughly examine, and the temporal limitations of study proposals in such a rapidly changing landscape, it is also important to touch upon those areas of the vast field of utility feedback that it this paper will not thoroughly evaluate.

Pricing Structures

Electrical usage feedback regimes present a strategic opportunity for electricity management at a time of fast change in domestic energy policy in the US. Since usage feedback may merge elegantly with social norm and dynamic pricing strategies for electricity use, a synopsis of study in these fields is necessary.

Researchers and private entities have made promising findings involving dynamic pricing of electricity to control peak demands (Asadinejad and Tomsovic 2017, 216), while research into social norms and electricity consumption has shown the potential for consumer awareness of typical use to reduce wasted energy (Allcott 2011). Since consumers' response to real electricity price depends on their exposure and access to both the price of electricity, and the cost of their actual usage, dynamic pricing and feedback go hand-in-hand, with disaggregation offering potential for consumer responses that reduce usage. A well-designed study may investigate the potential for a "multiplier effect" of feedback regimen that combines the best practices established by research in feedback (of which disaggregation information should be a part) and dynamic use. In the statistics field, this phenomenon is identified as an interaction effect. So this research must discuss some of the findings studies of dynamic pricing and consumer elasticity with respect to electricity, and some of the features of studies in reinforcing social norms. However, this research will bring in basic findings to facilitate a discussion of the potential for DEU feedback and design inquiry. Thus, the synthesis of academic findings with respect to dynamic pricing and social norm studies will not be exhaustive.

Implementation Cost

Electricity providers have designed and launched numerous pilot programs (some involving research institutions) in attempts to answer a range of behavioral questions about utility consumer behavior and potential savings (Molina 2014). Additionally, much of previous electricity and other utility use research is aimed at finding cost-efficient interventions with the guiding question: how much usage can we save, and is it worth the cost of implementation? Thus, there is a body of proprietary knowledge surrounding these cost curves, and while some technological options will be discussed, cost/benefit analysis should be left to those with the knowledge and data resources to make those assessments. Electricity providers, governments and other groups with access to their proprietary data can perhaps come to a better assessment of the value of given reductions in peak or overall demand in a particular load zone, and compare those savings to specific per-household implementation and management cost.

Additionally, rough estimates of implementation cost will offer justification for a pilot that would mirror a larger roll-out, and the pilot itself will offer further insights not only on technological feasibility, but also on management costs, potential cost overrides and other study complications. It is expected that a pilot will serve as an intermediate step within this larger study proposal to clarify potential costs of such a larger study and, eventually, to wider, perhaps population-wide, deployment. Hardware and management support costs would likely be determined through contractual negotiations with manufacturers, and these negotiations would potentially benefit from both the findings of a pilot study, and the mutual advantages of bulk purchasing of hardware.

Engineering Concerns

This examination seeks to offer a study design that has specific and significant software demands, and potentially significant hardware engineering demands as well. While commercially available products exist that offer various types of feedback and analysis, some manipulation of their feedback design is at this point necessary to meet the demands of a study, since these technologies typically feature a dedicated interface, and data collection methods for the purposes of a study are not necessarily built into existing systems' technologies. Once again, the costs and limitations of software and hardware design are beyond the scope of this academic inquiry, and are achievable only through negotiations with software developers and various equipment providers. An incremental approach with modest engineering demands and a small number of installations is expected to offer significant evidence as a proof-of-concept that such a wider study, with more comprehensive software design and a more extensive data management structure, is possible, and can offer useful results.

Regarding costs associated with actual study features, there are numerous permutations available to study nearly the entire range of energy feedback mechanisms, disaggregation, and time-of-use mechanisms. Each permutation comes with its own separate design and management costs, but preliminary and replicable iterations to test the feasibility of a wider study can choose which and how many of these to include. Additionally, observing the rapid pace of development in the energy monitoring sphere, it is possible that systems close to those proposed in this paper will be developed. For example, there has been increasing demand for energy monitoring technologies to offer wider interface options, including cost units, as opposed to presentation of usage in units of electricity consumption.

The Common Nature of Utility Use

We should consider a few features of overall utility use in the home, lending support to the idea that feedback regimes for electricity can be widened to incorporate other utilities (heating fuel, water, etc.) in the home if there is an ability to integrate monitoring technology with those other utilities.

As mentioned previously, electricity is not an end-use, but rather a means to produce kinetic energy, lighting, heating and cooling, etc. With this conception in mind, it is useful to recognize that other utilities in the home (heating fuel, natural gas, water, etc.) overlap significantly in the sense that they are consumed to facilitate end-uses, with the common measurement of their consumption being dollar-cost. For example, the cost of a gallon of hot water is essentially the combination of the price of the water itself and the fuel (electricity, natural gas, etc.) used to heat that water. From a consumer standpoint, the important consumption factor in the decision-making process is the total end-use cost of it, and users are likely agnostic with respect to quantities of source fuels and other inputs that produce the good. Still, this relationship between behaviors and the costs of those behaviors is hidden for most consumers.

This obstruction means that since the various resource uses in homes overlap so often, DEU feedback as a stand-alone still arrives as only a subset of our relationship between our consumption behavior and price. Household monitoring should eventually make the logical jump to overall utility use, rather than to uncomfortably carve out just one input into household utility costs. But the principles of DEU feedback and the findings of studies in this area in many cases may translate to other end-uses in the home (to the extent that those end-uses can be priced, monitored and displayed). Keeping in mind that the homeowner may input cost and receive benefits similarly across a range of household utilities, we can extract insights from studies that are not explicitly focusing on electricity use, and make some assumptions about the wider utility implications of our findings. Our final proposal will discuss electricity usage feedback, but will not address the implementation challenges or a wider-range utility monitoring structure. Though applying DEU feedback lessons to other forms of utility use may offer broader insights into household behavior, we will not attempt to extrapolate these lessons to other areas of utility use.

CHAPTER 4: METHODS

Conceptually, this investigation is the culmination of studies that began in early 2016, and new sources have been published since the beginning of this research. Major search engines for source material included Google Scholar, Web of Science, Science Direct, and IEEE Xplore. Tufts JumboSearch offered an additional resource for locating source material, especially for subsidiary topics. Google's web search engine was the avenue for some primary source material, including information from federal agencies including US EPA and the Energy Information Administration.

Starting search terms included "electricity AND disaggregation AND feedback", "energy monitoring", "electricity OR energy AND feedback AND efficien*" While sources were surveyed from as far back as the 1960s, policy and technology changes in recent years necessitated a focus on sources published in or after 2010, with special emphasis on reports and academic research from 2014-2017. For study design research, most insight and guidance came through reviews of previous studies in the field, and several papers focused on electricity feedback study design considerations and recommendations.

Research opportunities in such a rapidly evolving research area also represent a challenge. Sources are constrained by a rapidly changing environment: many recommendations in this field face looming obsolescence, as new and constantly expanding research at times supersedes work published just months prior. As an example of this dynamic research environment, some sources cited herein have been published just a few months, prior to this paper's publication.

Most source material was grounded in peer-reviewed journal articles. There is a wealth of evaluation reports on efficiency programs and electricity feedback programs performed by privately contracted consulting groups, however these reports do not approach the intellectual rigor of formal academic research. They are considered more for their methods and observations, less so for their results; and their conclusions are viewed with some skepticism on the part of this author.

CHAPTER 5: CHALLENGES TO RESEARCH IN THE FIELD

Changing Policy and Technology Landscape

Electricity monitoring is a burgeoning area of inquiry, with policy, research and technological horizons changing regularly. It will be important for this investigation to assess and present the technological resources that appear accessible now, and in the near-future. The fields of computer science, engineering and statistics are regularly refining algorithms, designing and building new hardware, and bringing new analytical models to this area of study. Thus, any assessment of this author's findings, and the field in general, must be examined in that context of the future in which the assessment occurs.

The future of energy innovation is perhaps more uncertain and unpredictable than the evolution of energy monitoring technology. Many sub-areas of energy production and use are experiencing rapid change. These include changes in fuel technology and pricing, advances in energy storage, the changes in the types of fuels we are using for electricity generation, transportation and other energy areas, potential advancements in nuclear, renewable, and conventional energy production (Nyquist 2016; Howard 2015). Predicting how, where and from what sources we will derive our energy in even the medium term is a trillion-dollar question with evangelists and skeptics on all sides.

All this brings to mind the adage that the only thing constant is change. A decade from now we could be using our automobiles as batteries to support the grid. Our mass transit could be powered by hydrogen; urban electrical needs could be supplied by nuclear micro-grids; smart appliances could work while we sleep; and households could store solar energy on-site for use at night. Advancements in emissions capture could allow us to renew our love affair with coal and oil without the environmental and public health problems that strain the relationship today. Carbon taxes or other energy tax regimes may be employed on a national or sub-national level, changing the fundamental economics of energy consumption. While the possibilities are infinite, it is also possible that few or none of these technological advancements, social trends, or policy changes will happen within the decade or even the next several decades.

Investigating in a Changing Environment

This uncertainty does not, however, support a “wait-and-see” approach. The rapidly changing landscape rather presents an opportunity and an imperative for new research in consumer behavior and energy feedback. That is because most research in this area investigates the human element and our interaction with technology. With the clear and consistent findings achievable through new research, we can then connect the energy needs and preferences of consumers with the technological capabilities our electrical infrastructure offers. Further, a comprehensive understanding of how households react to various inputs will provide us with future policy guidance. And a better understanding of methods for influencing household electricity usage patterns (as well as the limitations of these interventions) will serve as an important baseline around which we may calibrate future energy planning and management.

To encourage sustainability, we need to learn how people use electricity, how they waste it, and how they react to its price. We need to learn how flexible households are in their usage patterns, and the effect of various combinations of ways to connect people to their power. Finally, we need to combine this new knowledge to create efficient ways to change peoples' usage. This knowledge base will be a crucial step in developing a cost effective electrical grid that supplies power as efficiently as possible from an economic and environmental perspective.

It should be noted also that properly designed studies in this arena are likely to have relevance regardless of whether they achieve statistically significant change: we seek a clearer answer to the question of what the possibilities are for feedback in various forms to influence our usage patterns, and while there is significant evidence that some forms of feedback produce beneficial changes in household usage, a more detailed comparison of those various methods across a common platform is lacking: should interfaces be more complicated and detailed, or simpler? Does real-time feedback present advantages over incremental assessments of previous usage? Does disaggregated, appliance-level feedback offer advantages over whole-home usage, and to what extent? What combinations of these methods of presentation might prove more effective? What variances in effect exist across the many feedback methods, and how do usage changes (by overall usage, appliance-level usage, or time-of use) correlate with other household characteristics? What types of elasticities do we observe in these same areas? How does dynamic pricing feedback interact with all these various methods? This exploration will not attempt to answer these questions directly, but rather will try to establish what is currently known, and how we might learn a great deal more by keeping these questions in mind as we proceed.

CHAPTER 6: INEFFICIENT USERS AND INEFFICENT HOMES

Standby Waste

There is observational evidence that a great deal of electricity is wasted in the home in various ways. For example, entertainment, information and communication devices, (computers, televisions and audio devices, etc.) account for nearly a quarter of home electricity use. But 30% of that use is consumed when these devices are on standby (Rowlands, Reid, and Parker 2015, 391). That means that over 7% of total household use is consumed by entertainment devices while we are not using them in the form of computer fans humming, televisions on standby, etc.

Discount Rate

Some of the uninformed consumer behavior around electricity can be attributed to the **consumer discount rate** – essentially the observed economic behavior whereby consumers value present dollars at a greater level than future costs, and thus appear treat future costs as less impactful than present costs. (Berns, Laibson, and Loewenstein 2007) In looking at electricity consumption, there is evidence that consumers apply large discount rates to future consumption when considering the purchase of appliances (McCollough 2010, 187). Jacobsen (2015) observes that while consumers do display longer-term responses to electricity costs, their appliance purchasing decisions are not necessarily motivated by that same consideration. Some social surplus may thus be lost by consumers making suboptimal purchasing decisions that ultimately lead to reduced use of these less-efficient appliances. (Jacobsen 2015, 94–95). In other words, some consumers may pay a lower cost for an inefficient appliance, and may later on restrict their use of that appliance in part due to the cost of operation. While an optimal scenario would have involved greater use of a more efficient appliance, these consumers find themselves paying more in overall cost for less use.

Behavioral Change

Fischer (2008) provides the most apt analysis of the behavioral element of consumer utility and electrical use: electricity faces the challenge that it is invisible both physically and conceptually. It is not an end-use, but rather a means to facilitate household and societal needs. To raise awareness, Fischer explains that behavioral change must be precipitated by conscious decision that then becomes "routinized", or built into our daily habits (Fischer 2008, 81).

The Role of Salience

This discussion of the discount rate can be extended to regular household use decisions. Although households implicitly understand that they are responsible for costs of their utility use each time they use it, we can infer that there is an element of discounting that occurs: since the typical exercise of electricity use is not as noticeable as inserting money into a coin-op laundry machine, but rather is assessed and paid monthly, there may be a reduced sense of real cost. It is reasonable to assume that households apply some form of a discount rate to utilities used today but which are paid for next month. While there is some evidence that reduced visibility of cost increases usage (and as such leads to sub-optimal household decisions) on a month-to-month basis (Sexton 2015, 229-230), the gap between daily or momentary use and monthly payment has not been sufficiently studied.

The Spectrum of Awareness

Since electricity usage awareness and salience is in some cases correlated negatively with usage, consumers can be thought to operate on a spectrum of awareness where households with lower awareness (little to no exposure to the cost of electricity usage) correlate in some fashion with higher average usage, and high awareness households correspond to lower use. But this spectrum is not likely to be linear as more detailed and more regular feedback is presented to households. Rather there are likely levels of awareness where households will make significant gains with a modest increase in awareness, and other levels where potential gains are lower. In order to evaluate the potential impacts of various levels of feedback interventions a real sense of this "awareness curve" is necessary (for more, see Appendix). While the study proposed here does not provide a full-scale evaluation of all levels of awareness, it does attempt to definitively examine a few of the most important “jumps” in awareness, from aggregate to disaggregated feedback, from baseline to real-time feedback, and from baseline to incremental usage feedback.

CHAPTER 7: ELECTRICITY MONITORING RESEARCH - PAST AND PRESENT

Early Work in Electricity Usage Feedback

There has been a substantial amount of study dating back to the 1970s and 1980s regarding consumer responses to home-level electricity and utility use. These studies have found the possibility for real savings as the level of exposure becomes more clear, granulated, and immediate (Midden et al. 1983; Hayes and Cone 1977; Faruqui, Sergici, and Sharif 2010).

The first substantive study on the effect of household exposure to DEU feedback was by Ontario Hydro (1992), using dedicated desktop computers placed in the home to display usage of several appliances (Dobson and Griffin 1992). The Ontario Hydro study found that consumers reduced their consumption by up to 12.9% over control groups (Dobson and Griffin 1992). But like many early studies in this area, there were design limitations as well as issues with replicability. For example, there was no consideration of how much any increased attention to the feedback was simply a function of a new (and expensive) desktop computer being placed in the home.

As to replicability, the Ontario Hydro study offered little in terms of potential for wider-scale interventions, since the installation was cumbersome and equipment was costly. But through this and other earlier studies we see an early bifurcation of the areas of inquiry in usage feedback. The Ontario Hydro experiment was, like many other studies, intended to study human behavior, rather than to evaluate a potential demand management innovation technology for wider roll-out in homes. The two inquiries offer similar but distinct sets of questions – the first being, “how do households respond to feedback?” and the second being, “what kind of system to change household consumption habits will be feasible and effective?” We see throughout past research in the field that these two areas of study – one testing consumer behavior in an idealized and non-replicable scenario, and another evaluating the impact of real-world, available systems - have been investigated through separate studies. Thus, most behavioral research has been unable to translate to real-world interventions, and those studies using these real-world accessible technologies have produced limited conclusions about the relative impact of various feedback regimes.

Recent Analysis

Kelly and Knottenbelt (2016) performed a systematic review of 12 known studies on DEU feedback. The researchers’ motivating questions in their analysis were to what extent DEU feedback can aide reductions by a subset of energy-aware “enthusiast” households, to what extent these potential gains will translate to the general population, and whether DEU produces savings beyond whole-home, aggregate usage data. They also did some analysis on effects of the level of detail of disaggregation, and whether the granularity of the data was important to its impact on consumer behavior.

They suggest that while this DEU feedback is observed to reduce electricity usage by an average of roughly 4.5%, they were not able to arrive at a statistically significant difference of effect between DEU feedback and whole-home feedback (Kelly and Knottenbelt 2016). Their findings, however, are tempered by a few concerns within their assessments, both in that the treatment groups in studies comparing disaggregated and aggregate feedback had unequal exposure to feedback, and that the typical arrangement observed a reduced frequency of exposure among participants in the disaggregated group than their counterparts in the aggregated group (Kelly and Knottenbelt 2016).

The most prominent example of varying levels and types of exposure to information among treatment groups incidentally offers the largest sample size known of a study comparing disaggregated and aggregate feedback methods. In 2014, subsets of 1,685 customers of the utility company Pacific Gas and Electric were either given web access to disaggregated information via a Bidgely system, or an AzTech in-home display (Nexant 2014, 38). These different interfaces resulted in dramatically different exposure, as the aggregate group viewed their

IHD an average of eight times per day, while the disaggregated users accessed their information via web an average of once per day (Kelly and Knottenbelt 2016). While the study could be deemed effective in comparing usage effects of two existing systems of feedback, the large differences in feedback medium created an imbalance in exposure between the two treatment groups, limiting researchers’ ability to make assertions about the relative conservation values of aggregate and disaggregated feedback.

CHAPTER 8: PREVIOUS STUDY LIMITATIONS

Disaggregation research has been done almost exclusively using the antiquated, cumbersome monitoring technology and complicated (or problematic) feedback interfaces that were available at the time. Beginning in 2015, inexpensive, easy-to-install, user-friendly technologies that not only provide disaggregated feedback but also collect data on user interaction have become commercially available (Talbot 2016; Kelly and Knottenbelt 2016). These technologies fundamentally change the research landscape for energy disaggregation and consumer behavior due to their low cost, their simple implementation and interface, and quality/accuracy of data. Today we have the potential for large-scale, real-world applications of DEU feedback, but the technology's potential impact on consumer energy use has not yet been adequately studied.

Distinct from the appliance-level or circuit-level analog devices that prevailed in the market until just a few years ago, electricity disaggregation technology today involves a device and algorithmic program that gathers and provides detailed and in some ways, itemized electrical usage data for a whole household (Hosgor 2015). These systems can provide real-time and historical use for the majority of the appliances in the home.

Scalability

Kelly and Knottenbelt (2016) identified that among the studies they reviewed, roughly half used IHDs that were more likely to capture consumers' attention than displays that would make up a scaled roll-out of the technology. Their finding highlights an important distinction researchers should consider in study design. While previous studies sought to learn insights about consumer behavior *or* device/system effectiveness, current technology allows us to study the medium *and* the consumer simultaneously, so that studies can have real and reliable implications for policy, *and* can be refined through adjustments in software.

Technical Accuracy

Accuracy of NILM technologies has been a recurring concern for researchers (Jain, Taylor, and Peschiera 2012, 15) and Low-quality disaggregation data was said to cause skepticism in some study subjects (Kelly and Knottenbelt 2016). In some instances, researchers characterized their data collection as inaccurate or incomplete, in most cases due to technical error such as monitoring equipment failure, or design limitations such as insufficient sensitivity of monitors (Rowlands, Reid, and Parker 2015). Recent technologies, notably the evolution of disaggregation algorithms, have improved accuracy of NILM to recognize various uses to over 90% (Ahmadi-Karvigh, Becerik-Gerber, and Soibelman 2016, 346).

“Opt-In” Selection Bias and the Characteristics of Study Participants

Due to the intrusive nature of household studies in general, and utility usage studies specifically, privacy and other ethical concerns lead to a significant barrier to studying household feedback through randomized controlled trials (Neenan and Robinson 2010, 4.22). Thus the vast majority of research in this area has been confined to observational studies which must use opt-in methods to select participants (Rowlands, Reid, and Parker 2015, 386).

An as-yet unresolved controversy/research gap is present in energy monitoring and disaggregation research, related to assumptions that researchers and eventually policymakers make around the intrinsic characteristics of households who choose to enroll in an energy study. Since many logistic, ethical and privacy issues are present in subject selection of household studies, there is a deep concern expressed in many studies that these households are non-representative of the general population (Neenan and Robinson 2010, 7.3), and thus findings of a study group’s response to any intervention is viewed with skepticism about its wider implications.

Rowlands et al. claim that “technophiles” populate much of the volunteer bases of the studies they examined (Rowlands, Reid, and Parker 2015, 391) while Kelly and Knottenbelt (2016) assume that “energy enthusiasts” make up the majority of the feedback-based study populations, since participants in nearly all those energy studies are selected through an "opt-in" process.

But researchers who have conducted these reviews of existing studies tend to make inappropriate assumptions about the bias introduced through an opt-in selection process. Specifically, they broadly assume the "energy enthusiast" or "technophile" household will invariably offer greater potential for savings than will an average household. There are many cross-currents here that make that assumption hard to substantiate without granular study of the characteristics of these sample populations.

It is possible that technophile/enthusiast households are more energy aware to begin with, and have thus already employed some of the basic interventions that can easily produce energy savings, such as purchasing efficient appliances, replacing incandescent lighting with LED or CFL bulbs, adjusting temperatures on electric water heaters, etc. If these aware households are disproportionately closer to optimal electricity use, then their potential for energy reductions in the presence of better information, especially those "low-hanging fruit" interventions, is lower.

It appears the basic concept of changing consumer behavior around utility use is a synergistic increase of education and awareness – to get households to understand what they're using and what it costs, and to get people thinking about their use on a more regular basis. It is as valid to assume that enthusiast households would have a better basic understanding of their electricity use and may have made positive interventions due to their pre-disposition, as it is to assume that they would be more responsive to new usage information. The true answer to this question of the selection bias effect of aware households is that we do not know the balance of biases it introduces, positive or negative.

Among these more aware sub-populations, there may be a correlation between efficiency interventions and likelihood of opting into an energy study. This potential correlation could in fact create a *negative* bias in results, since these aware households may have a lower potential for further savings. This potential negative bias does not appear to have been sufficiently vetted within the academic research.

Uptake Concerns and Unequal Treatment Groups

Many researchers also highlight the problems with uptake with various studies, specifically that study subjects do not interact with some study interfaces often enough, or at all, thus diluting the study-wide effects (Kelly and Knottenbelt 2016; Vassileva et al. 2012; Nexant 2014) . This imbalanced exposure points to errors in study design, but uncomfortably straddles the two distinct lines of inquiry discussed earlier, consumer reaction to disaggregated energy consumption exposure, and those technology and awareness techniques that can be studied, modified, and rolled out depending on study findings. The first question of the general potential for these types of interventions is an important one which of course precedes the second; however due to technological advancements, most research into scalable models has become largely obsolete.

One research team made a counterintuitive finding in the available studies that compared DEU with aggregate usage feedback, identifying that DEU feedback may offer little advantage in usage reductions over whole-home feedback, and in some cases showed to be *less* effective (Kelly and Knottenbelt 2016). However this assertion returns to the issue of whether the subject of the inquiry is consumer response or efficacy of exposure methods – in two cases synthetic data was used and participants voiced skepticism about the accuracy of usage information; and in one of the largest and most comprehensive studies in this field, the two groups (disaggregated and aggregate) were given very different interface methods, with the aggregate group given an IHD and the disaggregated group given an online portal. Understandably, the disaggregated group was shown to have visited the online information only a fraction of the number of times the aggregate group interacted with their IHD (Nexant 2014).

The gulf between these two research questions has only now been bridged by advances in consumer technology: for the first time in the several decades of household energy use study, designs that attempt to establish an ideal measure of household response to electricity usage of, and the testing of household response to a scalable system of delivering electricity usage are the *same*. The most cost-effective, easily deployable study technologies are also likely the most accurate, comprehensive and easy to manage. This is because these household systems are designed for the consumer market, and because data output and management is designed to maximize both the consumers' understanding of their energy use and the company's synthesis of the data(Talbot 2016). While the proposed study here suggests some modifications and a new method of feedback, these changes are a matter of software design, rather than broad technological advancement.

Backsliding: Hawthorne Effect and Regression Gains Over Time

Schwartz et al. (2013) found real evidence of the Hawthorne effect in energy consumption studies, indicating that study participants' behavior was influenced at least in part by their knowledge that their behavior was being observed as part of a study (D. Schwartz et al. 2013, 15244). The Hawthorne effect can increase bias in behavioral studies (typically in a socio-normative direction) thus limiting the confidence with which we can extrapolate study findings to a wider population (McCarney et al. 2007, 8). In DEU and other household utility usage studies, the observed electricity use reductions by a treatment group in a study may not be expected to be achieved when the treatment is expanded to a wider population. This is in following with the main features of social norm programs like those adopted by some electricity providers, where a comparison of a household's consumption relative to their neighbors or equivalent households can act to reduce their consumption (Allcott 2011, 1085).

"Backsliding," or the impermanence of behavioral changes over time is another issue somewhat related to concerns of the Hawthorne Effect. There is an observed tendency for participants' behavioral changes resulting from a utility usage feedback study to diminish over time (Allcott and Rogers 2014, 3006), and this potential is often not captured in feedback studies which may last for only a few months (Hargreaves, Nye, and Burgess 2013, 127). Additionally there is an observed tendency for participants to begin to "background" or in some sense pay less attention to IHDs over time (Hargreaves, Nye, and Burgess 2013, 127, 129). The organization known as OPower employed a social norm and usage method using monthly energy reports sent to electricity customers through conventional mail. Their research showed that even after two years of treatment in receiving reports, when households stopped receiving reports, the usage by program participants began to drift back toward their higher, pre-treatment usage levels, with their reduced usage regressing by 10-20% per year. But those treatment groups that continued to receive reports sustained their usage reduction with relatively little regression (Allcott and Rogers 2014, 3004).

This issue of backsliding brings up several important features to consider in study design: a study should be designed so that it is scalable to the wider population both in terms of technical implementation and management, and in terms of socio-behavioral influence. In other words, study participants should have an experience as close as possible to that of consumer households as part of a wide-scale roll-out, to give researchers greater ability to estimate what will occur if an intervention is applied to the real world. Namely, there should be a consideration of the need from an aesthetic standpoint to keep participants interested and engaged (Rodgers and Bartram 2011, 2495). A challenge of IHDs in achieving sustained household behavior can be overcome by regularly scheduled interaction through prompts (Bartram 2016).

CHAPTER 9: FRAMEWORK FOR A NEW STUDY

Advances in technology in the field may contribute to more comprehensive and higher quality studies due to greater ease and efficiency of implementation, making the management of larger groups easier, and making study participation less onerous. Rowlands et al. suggest that emerging technology will allow for better design of recruitment strategies as a way to increase sample sizes and reduce selection bias, and will offer better quality disaggregated data. (Rowlands, Reid, and Parker 2015, 391).

Current Tech: Available Systems

There are a wide range of offerings that have been commercially available to allow homes and businesses to monitor their electrical use in different ways. Numerous inexpensive devices such as “Kill-A-Watt” can provide monitoring of single appliances or groups of appliances plugged into a single power strip, and have been available for decades (P3 International 2017). More recently, inexpensive “in-line” devices can monitor outlet-level energy use and transmit that information via Bluetooth to offer feedback on a computer or smartphone. Other technologies provide households and businesses with real-time whole-building energy use monitoring, giving homeowners easy and low-cost options to provide some measure of electrical usage feedback. Some of these interventions are integrated with “smart meters” which record electricity use and transmit meter readings digitally to the electricity provider. Currently several companies offer feedback via whole-home use monitoring and in some cases provide estimated data through smart meters (Weliczko 2013). Opower, as discussed earlier, has in addition to experimenting with comparing customers usage with that of their neighbors, has worked with electricity providers to employ various methods of consumer feedback, measuring whole-home use through smart meters, and in some cases providing estimated appliance-level usage. (Allcott 2011, 1082). “Bidgely” works with existing smart-meter technology to provide similar disaggregated data and to offer management options for consumers (Nexant 2014, 5).

More recently companies have begun to offer DEU monitoring and feedback of household electricity use at the appliance-level. Devices like “Sense” (www.sense.com), “Neurio” (www.neurio.com) and systems like “PlotWatt” (www.plotwatt.com) and “EEMe” are a few such technologies that are connected to the central junction box in the home or business, and connected via Bluetooth or WiFi to provide detailed information on the time, usage and ultimately, cost of various appliances throughout the house.

The range of technologies currently available offer different specific qualities and feedback methods, and span a wide range of cost and accuracy. Commercially available at least since 2014, there are currently over 30 products on the market today that present some measure of disaggregated feedback (Kelly and Knottenbelt 2016).

The IHD market merges with these technologies, as several companies have produced IHDs that act as a dashboard for home energy use for at least several years (Rodgers and Bartram 2011, 2489) New technologies developing similar approaches are regularly becoming commercially available, indicating the potential for a competitive and variegated market (Bartram 2015, 57).

Studies like the one proposed here were unrealistic from a technological and cost standpoint until just a few years ago: today, accessible and easily installed technology can combine with a more modernized information system to create a study that is cheaper, less prone to bias, easier to conduct, and as we will discuss, replicable for a wider roll-out at the electricity company level.

Cost Considerations: Is Disaggregation Worth It?

Though DEU feedback may have some effect in reducing use, considerations for wider implementation will likely be made around cost efficiency, comparing the magnitude of impact of an intervention to its implementation costs. Efficiency programs need to justify their costs, thus the Opower model using inexpensive mailings is easily justified. More hardware intensive and human-capital intensive programs thus face a significantly higher bar of returns. Evidence suggests that there is a standard of electricity savings on a cost-per-kilowatt-hour basis. Most electricity efficiency programs in the US cost roughly $.028 (2.8 cents) per kilowatt-hour savings, with higher end costs at $.05 (5 cents) per kWh (Molina 2014, 29). A further challenge to a capital-intensive program is that significant start-up costs are subject to a discount rate in themselves of 5-7% (Molina 2014, 7). So programs with significant startup costs face a higher standard of results, since their projected energy savings over several years are diminished by significant reductions in net-present benefit.

The performance standards of efficiency programs may be changing as well as the nature and markets for electricity, but technological costs and capabilities are also a moving target. Thus, these cost/benefit evaluations must be made after realistic assessments of start-up, implementation and management costs have been made.

CHAPTER 10: THE ROLE OF A NEW DISAGGREGATION STUDY

Previous studies have attempted to test the behavioral effectiveness of real, existing feedback systems, while others have tested disaggregation from a behavioral perspective rather than retaining consideration of real-world applications of study findings. Today, we are nearing an opportunity to effectively examine replicable regimes and compare various feedback regimes *simultaneously*. A single study testing responses to a range of feedback methods using a replicable, scalable system offers the potential to arrive at more definitive conclusions on the relative effectiveness of these various methods, while offering actionable guidance for wider implementation of feedback systems

Selection Bias Does Not Have to Be a Problem

There are few good methods that might counter selection bias, however the framing of the study does not need to correct for this, depending on the method of the study's roll-out as it might relate to a wider program. If, for example, an electricity provider partner were to choose a random pool of 1,000 customers to recruit to participate in a study, and received a response that was a subset of 100 members from that random group who participated, and those participants reduced their electrical use by 7 percent[1] the findings of the study could be extrapolated: for every customer recruited, 10% will sign up, and participants will reduce their consumption by an average of 7%, or 0.7% of the recruiting pool, with implementation cost being the sum of design costs, the cost of the recruitment effort, and the per-household cost of implementation for each participating household.

Replicability and Study Design Opportunity

Current technology allows us to perform a study with real-world applicability expanded to thousands, or even millions of households while using a similar medium across treatment groups. If our experimental design prioritizes replicability, we will not be asking and answering only theoretical questions, nor will we be limited in our ability to assess various feedback methods and levels. Rather we will be able to develop reliable estimates of which interventions cause changes in usage behavior, and to what extent. If we can come up with confident estimates of returns from such a system, we can develop cost-curves comparing implementation costs with usage reductions (and with dynamic pricing, usage shifts), in order to develop a firm idea of what level of cost associated with the program will justify its roll-out.

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[1] It is likely that with a utility as a partner, there would be no need for a control group, since the utility can extract control data from its existing accountholders. There is some precedent for this in other utility-use studies.

Complementary/Multiplier Effects

Investigation of a potential multiplier effect of multiple treatments is motivated by central question: Is the whole greater, less than, or equal to the sum of its parts? If we can establish from existing literature that various electricity feedback interventions can each produce some usage reductions, what is the total effect when they are applied together? Will households save more when exposed to multiple treatments simultaneously? Will these multiple treatments complement each other, resulting in greater cumulative savings from multiple methods used in concert, or will employing multiple methods together be redundant?

Several classes of interventions to reduce household energy use have become popular in policy and research circles, and usage feedback in its different iterations is only one. As mentioned earlier in the paper, Opower and other electricity providers have begun to roll out programs whereby customers are informed of their electrical use relative to their neighbors and/or equivalent households through low-cost mailings or alerts via the internet. (Allcott and Rogers 2014, 3012). Dynamic pricing, Time-of-Use (TOU) pricing, demand-side management programs and other similar programs employ temporal variations in the cost of electricity in an effort to incentivize customers to use less electricity during peak times, when excess power needs are met by exceedingly expensive power generation (Asadinejad and Tomsovic 2017, 216). Social comparison, which can be low-cost and non-resource intensive, has been shown to reduce overall usage by roughly 2.5-3% (Lossin, Loder, and Staake 2016, 151; Allcott and Rogers 2014). TOU pricing structures have been shown to significantly reduce peak consumption (and in some sense reduce GHG emissions and net electricity costs) (Greer 2012). Aggregate feedback regimes have been shown to reduce electrical use by roughly 3% (Kelly and Knottenbelt 2016).

There is some reason to believe that these various types of feedback and influence may complement each other, and as discussed before, pricing structures and detailed feedback may work as complements: detailed feedback can be a tool to allow better response to price variations, and those price variations themselves may bring greater awareness to households. This form of an *interaction effect*, as it is known in statistics, is key to making assessments of which types of usage-reducing interventions to implement – two or more methods of intervention employed simultaneously might be redundant (negative interaction) or complementary (positive interaction). Some interventions might each retain their effect regardless of the presence of other interventions (no interaction).

CHAPTER 11: ANCILARY BENEFITS OF FINDINGS

There is a potential for a greater integration in policymaking between electricity generation and end-use consumption. As renewable energy increases its role in supplying the grid and electricity storage becomes more economical, the granular data that constitute aggregate electricity use will allow for synergies between generation, storage and end use (Rowlands, Reid, and Parker 2015, 392). From an engineering perspective, a clear understanding of granular home electrical use could offer broad insights into home behaviors.

Carlson et al. (2013) assert that disaggregated electrical data can give more clarity to electricity providers about their customers, and that granular understanding can be a highly useful management tool. Rather than using average household characteristics, they may be able to use either actual home data or extrapolate more effectively to impact customers' usage behavior (Carlson, Scott Matthews, and Bergés 2013, 134) . Wider application of DEU feedback systems can show more clearly which types of behavior are more malleable, which types of electrical use are less temporally constrained, and which areas are typically sources of wasted energy. This knowledge may inform policymakers and electricity providers of the real potential savings from modifications in home design, building codes, and the technology associated with our appliances that will offer economic and social efficiency gains.

Customized Efficiency Ratings for Households

From a single-household basis, individual home usage patterns can offer each household clear economic projections on all their purchases. Currently, programs like EnergyStar and efficiency labeling offer electrical cost estimates based on broad generalizations about consumers (Jacobsen 2015, 96). In an environment where electrical use, and thus appliance use, is highly variable from one home to the next, those estimates have little realistic basis. Even so, a 2014 study on the effect of displaying cost information on light bulbs showed that consumers made more prudent long-term appliance choices when provided cost information as opposed to electrical usage information (Min et al. 2014, 48). A granular, disaggregated household electrical usage history could provide a very accurate projection of costs vs savings for many appliances. Knowing exactly how many loads of laundry a family ran in a year can lead to reliable numbers on the savings associated with energy-efficient appliances, and further, can provide a pathway for policymakers to award targeted rebates calibrated around individual purchases. Essentially, households may be more responsive to life-cycle savings if they are based on a household's actual usage patterns: rather than to assert that an efficient dryer will save an average home $52 per year over a less-efficient model, itemized usage history can inform individual households that if they use their new washer as much as they did in the previous year, the efficient model will save them *exactly* $52. It is not clear to what degree enhanced accuracy on life-cycle savings projections will precipitate better purchasing decisions. But since consumers value accuracy in electricity monitoring (Jain, Taylor, and Culligan 2013, 413), and since consumers are shown to make sub-optimal purchasing decisions with respect to efficiency ratings (Jacobsen 2015, 96), the potential savings of customized efficiency savings should be investigated via future academic research.

The above only begins the discussion of consumer purchases. Consider that knowing individual family usage habits around laundry, for example, could lead to encouragement (financial or otherwise) for certain households to purchase units that better fit their habits, for example machine units that perform both washing and drying, to allow the user to set the unit to run during the night, when electrical demand is low. For a family who does 30 loads of laundry per year, shifting a portion of washing machine use to late evening might represent insignificant usage reductions for the grid; however, it might be a significant planning tool for families who do 200-300 loads per year. Further, such units may not be feasible for homes that run several loads per day. Knowing usage patterns in this respect can offer far greater direction to households to make optimizing appliance purchase decisions, and can give them reliable numbers in terms of savings. Likewise, knowing households' real usage patterns around air conditioning, dishwashers, stoves and entertainment systems can give those households information to optimize their purchasing and usage decisions while giving policymakers indicators at the household level of the potential savings associated with various incentives, whether they encourage the purchase of new appliances, or provide benefits for shifts or reductions in usage.

Enhanced Understanding of Family-Level Behaviors

Since the electrical grid in the US is changing, we do not know the future cost profile and fuel sources of our electricity in any given geography. From a planning perspective, the increase in solar and wind generation has already changed the daily generation cost profile of electricity, and greater penetration will change the daily needs of other sources significantly (Janko, Arnold, and Johnson 2016, 47). Although some generation correlates somewhat to electricity demand (solar arrays produce electricity during the day and are especially productive during high demand events related to hot weather), increases in these sources of electricity represent a grid management challenge because of their intermittent output (Khatib 2014, 176). A concrete understanding of family behavior patterns at an appliance level will be a useful tool for planning future aspects of electricity load management. Additionally, understanding appliance-level elasticity will aid energy planners in the future around a range of efficiency interventions beyond feedback alone. For planning incentive, social norm or other types of energy management, planners will be able to more adequately target sources of efficiency if they have a better general understanding of what changes in appliance use occur when families save, and what behaviors result in which types of waste or inefficient use. While there are datasets currently available which capture household use profiles (Torriti et al. 2015, 893), there is a need for more representative data, as well as data collected where participants are subject to various treatments (Rowlands, Reid, and Parker 2015, 393).

Longer term energy savings may also be a direct result of enhanced energy understanding and awareness: some study subjects indicated that while certain usage behaviors were less flexible and not likely to change, knowledge of the electricity consumption associated with various appliances may foster their interest in purchasing more efficient appliances (Schwartz et al. 2015, 18–19). Because households likely make few if any major appliance purchases each year (Jacobsen 2015, 96–97), evidence of electricity savings from purchasing changes would be challenging to capture with smaller sample sizes and shorter study time frames; but larger study groups monitored over longer periods may provide some insights as to the potential effect of generally enhanced energy awareness.

CHAPTER 12: REMAINING CHALLENGES

Despite substantial advancements in the field, a few somewhat intractable problems remain in designing a new study. Two interconnected concerns persist: first, selection bias problems remain since controlled experiments are not feasible within the space. Second, ethical considerations remain at the forefront of any study that aims to collect such detailed information on household behavior, information that will be anonymized to researchers, but will be available to household members.

Remaining Selection Bias

The issue of selection bias looms large in these types of studies, because studies largely hinge on an “opt-in” model, where a self-selected group of participants signs up after being notified by the research group. Previous disaggregation feedback studies drew their participants from pools of customers who had already enrolled in other dynamic pricing or efficiency programs. While we understand that this opens the door for significant selection bias, the prevailing research speculates that this group disproportionately consists of those assumed to be more aware of electricity use and thus their reductions in electrical use may not translate to the wider population. The presumption that selection bias here creates a positive bias toward usage reductions may be an over-reach. "Energy enthusiasts" may present a paradox, since they may have already undertaken interventions to reduce their use (efficient lighting and appliances, reduced use of electric hot water, clothes drying, etc.). Thus, they may already be quite efficient, and their potential savings from increased electricity awareness may be limited.[2]

Provided we do not make the broad assumption that the opt-in bias is positive, we may have some tools to relieve some of our concerns about extrapolating energy study findings to the wider population. In partnership with an electricity provider, it may be possible to use aggregate, but real-time usage data from smart-metered homes to achieve a generally representative sample of the usage profile for the population. Researchers could compare that usage information to the patterns of a control group which as opted in but received no treatment. In effect, this fully unbiased usage information could offer a tool to evaluate the performance of a control group as compared to this more generalized but uncontacted representative sample of the population.

[2]As one anecdotal example, the author several years ago engaged in retrofits, behavior changes and condescending discussions with roommates, resulting in the electricity bill being cut roughly in half. Though I would likely sign up for an energy study, there are thus few remaining opportunities to reduce electrical use in this "energy enthusiast's" home.

Privacy and Ethical Barriers

While a study involving a randomly selected representative subject group within a population would eliminate the concerns of bias, ethical and legal issues largely prevent executing such a study. In collecting and analyzing a broad array of detailed information about household behavior brings up serious ethical considerations which may limit the ability to overcome issues of selection bias in study participants.

Collecting total disaggregated electrical use of a household is a form of surveillance – such monitoring will collect de facto information on the broad habits and tendencies of households: what time they wake up, how much television they watch, how often and when they wash their clothes, do dishes, when they come and go, etc. This information will not only be examined by researchers. Depending on study features, archived electricity use information could be accessible to some or all members of the household, affecting intra-family privacy. While some parents may see this as an opportunity to find out how late their children are staying up, how many hours of video games they play, or what types of activity occurred while the parents were gone, it could also be used for more nefarious breaches of privacy within the household. In any case, disclosure should be made to the family as to what information will be available to other members of the household.

CHAPTER 13: STUDY DESIGN CONSIDERATIONS

Studies in DEU feedback have produced a wealth of recommendations and considerations for future studies. These recommendations include suggestions on the scope of studies – what important gaps exist in the research and which questions should be asked to attempt to fill those gaps. Other recommendations point to specific design challenges in previous studies - from issues with recruitment to different styles of feedback medium.

While study design recommendations can be found in some of the earliest DEU feedback literature, this section will be centered around more contemporary research, since study design is informed by the technological conditions of the day, and more recent examinations of study design typically incorporate lessons learned by previous studies.

Participant Confidence

Accuracy is an important feature of any study, but clarity is perhaps equally important in retaining participants' confidence (and thus engagement) in the system. Past study participants have voiced skepticism over the accuracy of feedback and disengaged from the feedback interface (Kelly and Knottenbelt 2016). In other instances, DEU feedback that only appeared incorrect caused the same effect in participants, even though the information given was accurate (Schwartz et al. 2015, 18). Participants trust in the DEU feedback system is a crucial consideration for researchers. Study design should thus ensure not only that data provided to participants is clear and accurate, but also that it is perceived as accurate and reliable.

Clarity, Complexity and Customization

Participant interviews and surveys have also found a range of preferences of feedback (Bonino, Corno, and De Russis 2012, 392; Bartram 2015, 54). A 2015 study of Norwegian homes indicated that there was substantial variation among households purposes and depth of interaction with IHDs, with more affluent homes appreciating basic monitoring and tracking aspects of the home, with lower income and smaller homes interested in controlling their consumption (Westskog, Winther, and Saele 2015, 5446). Those studies further found that wealth correlated negatively with savings from reduced usage: less wealthy households showed significant reductions in use while wealthier households did not show significant gains (Westskog, Winther, and Saele 2015, 5431). This finding correlates somewhat with Sexton's (2015) finding that automatic bill pay correlates with greater increases in usage for lower income groups than for higher income groups.

Bartram (2016) asserts that while technology has enabled increasing detail of feedback, the complexity of presentation may have an opposite effect than intended. In addition to potentially adding to confusion and loss of confidence as mentioned before, the many dials, indicators, bar graphs and other features of a typical IHD dashboard may tend to overload participants (Bartram 2016). However several researchers have found that study participants are attracted to detail and an intrinsic interest in granular feedback, real-time usage and other analyses of their usage (Schwartz et al. 2015, 10–11).

Two concerns arise in study design when attempting to strike a balance between on one hand simplicity and ease of use, and on the other, sufficient complexity and detail so that participants remain engaged. First, to what degree do study design choices around a common platform, and the experience among participants affect different types of users? When we make study design decisions, we may be catering to larger reductions from certain groups than others. Second, to what degree may reductions be clustered in certain socio-economic subsets of the study population, with those reductions “watered down” by some subsets of users that show little or no reduction? This possibility would suggest not only the importance of including and analyzing richer baseline data about participants (demographic, socio-economic, geographic, etc.) but also that researchers should consider some availability of customization by participants, so that households may participate in choosing a medium of presentation that resonates with them, and hopefully results in greater engagement and savings.

A full factorial design which compares various treatments may offer some insights as to which interventions and combinations of interventions produce results based on sub-group. A full factorial (or fully crossed) experiment exposes each level of treatment for each variable to <u>all possible</u> combinations of all other treatments, allowing for evaluation of the effects of the individual treatments and the interaction effect between multiple experiments. A fully crossed experiment will allow the study to not only provide estimates of the effect of each treatment, but will also provide comparative analysis of these treatments, and will allow researchers to test for interaction effects. We will be able to gain insight as to whether multiple interventions deployed simultaneously (for example weekly prompts AND real-time feedback) provide added, independent gains in usage reduction, or instead, to what degree they overlap and are redundant. Further, any "multiplier" or positive interaction effect may be observed.

Researchers are unable to draw definitive conclusions about the relative effectiveness of feedback methods when those earlier findings have been produced in studies that differ widely in terms of their design. The studies referenced in this paper used a range of different interfaces and feedback methods and feature major differences in their participant pools, creating the possibility for features of each study design to invite bias in one form or another. Examining the effects of different interventions through a similar interface and single study design may bridge this large gap in research in the field.

Such a study will also allow researchers to examine any potential interaction effects of treatments deployed in concert, and may provide powerful policy and management tools: reliable estimates of the effects of different interventions (with widely varying implementation and management costs, in some cases) will lead to cost/benefit analyses that to date have been unreliable. A finding that multiple interventions are not redundant, or that they are complementary, would justify wider roll-out of more comprehensive feedback regimes, to the degree that these interventions will provide value in reduced usage. Conversely, the study may suggest with confidence that various interventions offer some measure of redundancy, and amount to different strategies for getting at the same level of savings, with limited value in deploying multiple interventions in concert. This finding would inform policymakers about the relative cost-effectiveness of these interventions, and may guide future research in the field towards other interventions.

Interface and Feedback Design

Researchers in DEU feedback have provided insights and recommendations of how feedback mechanisms should look and perform, and the advantages and disadvantages to various interface designs.

Location of the IHD within the home is an important consideration. Since these studies depend heavily on participants' regular interaction with the IHD, improper location, or locating the IHD in different places in the home could introduce bias into study results. Researchers typically allow study participants to choose the IHD location within the home, but have viewed the kitchen or living room as ideal locations for installing IHDs. This preference is because of the amount of time spent by members of the household in these areas, and because of the amount of consumption-related activity occurring in these rooms. (Rodgers and Bartram 2011, 2494).

The Schwartz study, which designed a monitoring and feedback system using existing interfaces within the home, found that participants prefer access via multiple different devices, including television, smart phones and tablets. Their study showed that the home television was by far most common device for using the interface, with other devices, including computer, smart phone and tablet use cumulatively totaling less than 10% of system interaction (Schwartz et al. 2015, 16). It is not clear to what extent the availability and sporadic use of smart devices fostered engagement in the monitoring system, or whether multi-device access was only perceived as an attractive feature.

To provide real-time usage feedback, researchers have used color-based visualizations in various studies in order to present real-time usage. Time-of-use studies have also used these visual aids to indicate high electricity-cost events. These color-based visualizations have been identified as easy to understand by most study participants (Bonino, Corno, and De Russis 2012, 390). Color-based visual feedback can be tested in conjunction with, or separate from other forms of feedback to investigate the variation in efficacy between real-time and incremental assessment.

While real-time feedback would seem the to offer the most salience, and thus produce highest response from participants, it does come with some complications. Participants receiving real-time feedback have sometimes developed skewed assessments of the cost of certain appliances such as hair dryers and toasters, because those devices produce large spikes in their usage while these devices are on. Participants sometimes fail to realize that the relatively short time these high-consumption devices are used means that they ultimately represent only a small fraction of the household's total electricity use (Bartram 2016). Cost figures given in real-time create a similar misunderstanding on the opposite side of the spectrum, since participants receiving real-time cost information see relatively small sums for even high use on an hourly basis. In their study comparing usage information presented in dollar units and kilowatt-hours, Shultz (2015) identified problems in their study in the perception of overall cost from real-time figures. They found no noticeable benefit to displaying cost information instead of in kWh. But they noted that a household's typical peak usage of .99 kWh would be displayed as costing just 36 cents per hour – a seemingly small amount of usage that translates to a monthly bill of over $200 (Schultz et al. 2015, 357). It is not clear whether consumers were able to adequately evaluate those real-time costs and extrapolate those instantaneous costs to cumulative costs experienced through a monthly bill. It brings some level of irony to the discussion, since this field's central task to aid households in making the cognitive leap to connect the cumulative and substantial costs of electricity use with their moment-to-moment actions, and to then modify their behavior according to their preferences.

Considerations for Determining Sample Size

Since we are running a controlled experiment, we may make an a-priori analysis on our ideal sample size. We would like to determine our sample size with an interest in producing the most meaningful and reliable results, however cost considerations for such a study loom large, and determination of sample size will be a compromise between these two competing interests, determined by the limits of researchers and funding. But to determine sample size of the study we can draw on findings from the previous studies in this field as well as general knowledge about study design, and suggest a power test with the values we have estimated. To run a power test to determine sample size, we will need to establish the following:

Estimated effect size – this is the lowest effect we would want to capture in our study findings.

We could base this number on the established literature on feedback, which shows various forms having an effect of **roughly 3%.** However, we may want to calibrate our estimated effect size using a DEU system cost analysis,[3] which could result in a potentially higher figure as our minimum value, but a higher minimum effect would require a smaller minimum sample size.

[3] An example may be helpful in illuminating this relationship of sample size to implementation cost of technology. We have cited earlier in this research that an average US home uses roughly 10,000 kWh per year, the minimum threshold of economic feasibility for an efficiency/use reduction program is roughly $.05/kWh, and the discount rate applied to cost of efficiency programs averages roughly around 5% per year

If an electricity provider were attempting to analyze a 5-year payback for a given intervention, we find that according to a 5% discount rate the provider would need to achieve annual electrical savings equal to 22-23% of total implementation cost.[3] Thus, an intervention resulting in 3% savings in electrical usage for an average US home could cost no more than $68 per home to fully implement. To approach this calculation another way, a $200 per-home implementation cost under these figures would be justified only if it resulted in an average usage reduction per home of over 9%. In the 9% scenario, researchers would input the 9% minimum effect, and produce a smaller minimum sample size, however the research findings would be largely unreliable if the real effect were below this number.

Significance Level (alpha, 1-tailed) - we will use a standard **95% significance level** for a 1-tailed test. We will use a 1-tailed test because there is no evidence in previous studies that enhanced electricity feedback correlates with increased usage, and there is no line of reasoning that would suggest that this is a possible outcome in the aggregate. 95% is a commonly used figure for confidence intervals in statistical analysis and essentially conveys that no more than one time in 20 would the results of our study produce a "false positive," producing a measurable result when in fact none exists.

Beta/Power – Our beta considers the opposite problem as our significance level, as it establishes the probability that we will falsely conclude that there is no effect when in fact one does exist. We will use a **beta of .05** (with a corresponding **power of .95**). This beta will provide high confidence in our results and limit the possibility for a "false negative", however it will require a larger sample size.

Selection Criteria, Sampling, and Participant Distribution

The chosen selection criteria are important to facilitate the mechanics of a study, but should be considered as a potential area for creating a non-representative study sample. While researchers should make attempts to cultivate a representative sample population, they should also consider the makeup of the sample population in their findings. For example, since an established billing history and likelihood of remaining at the residence for the duration of the study is essential, an important functional feature of study participants is an established residency history (minimum 2-years at residence, with intention to remain there for at least one more year). The selection criteria for the study, especially the criterion of residential stability, may lead to the sample being unrepresentative of the wider population. Definitive findings may be limited to households that meet those characteristics outlined in the study. Further, an unfortunate outcome of these selection criteria could be that wider roll-outs are limited in some way to certain demographic groups. Exclusion, for example, of lower income households presents not only an equity issue, but also an efficiency issue, since as explained previously, lower-income households may offer greater potential savings from feedback than more affluent households. Thus, the study should analyze and report the findings based on income, geography, family makeup, historical usage patterns and other features of the participant group, and analyze the potential variation in response between different demographic groups.

Additionally, a wider recruiting effort with the intent of a larger potential participating pool which could be pared down to a more representative group may provide more robust results, but may introduce other concerns of bias. It may be advisable to use certain characteristics to block study participants in various treatment groups, so that there will be evenly distributed usage history (high/low), income strata, geographic distribution, family size, etc. across the several treatment groups. If participants are blocked using a random method, it be unlikely to introduce bias into the study.

CHAPTER 14: STUDY OUTLINE

Hypotheses:

1. Electricity usage feedback results in more savings for households when feedback is disaggregated by end-use.
2. Electricity usage feedback results in more savings for households when feedback includes exposure to simple, real-time usage.
3. Electricity usage feedback results in more savings for households when feedback includes exposure to electricity interval usage (ex. How much was used per week)
4. At least one combination of these treatments has a positive interaction term – rather than offering different ways to achieve the same electricity savings potential, these interventions complement each other when used together.

In partnership with an electricity provider, households will be selected from that company's customer base. To recruit customers, mailings will be sent to homes identified by the company as having at least a two-year billing history. The research group should make efforts to recruit households from as broad and diverse a geographic area as possible. A broad population from which the sample is drawn will produce findings that will produce estimates pertaining to a larger population. Thus, partnership with a large and broad reaching electricity provider should be a priority.

Participant requirements will be as follows – participating households must:

- reside full-time at the residence
- have at least a two-year history at the residence and reasonably expect to reside there for the duration of the study
- have reliable household wireless Internet access
- have access to the household junction box, which services only that household
- pay their own electricity bill

Additionally, participating households will consent to the following:

- Allowing access to 1-2 years of historical electrical use data (possibly via allowing the research team to access their electrical utility account.)
- Consent by the household's designee (ideally the individual who is responsible for managing utility bill payments) to brief qualitative entry and exit interviews, wherein basic questions about household characteristics and energy use are asked, with a multi-fold objective:

- Establish baseline demographic characteristics to evaluate the sample against general population characteristics (income, family size, etc.)
- Develop an understanding of each participant household's energy awareness
- Identify any possible anomalies in historical energy use (air conditioning added, energy audit, new appliances, behavior changes, changes in household makeup etc.)

- Consenting to allow the research team to perform a brief electrical audit of the home including inspection of major appliances, and installation of appropriate monitoring hardware an in-home display (IHD) installed in their kitchen.
- Consent to receive color-based usage feedback, as well as alerts and notifications through the IHD
- Agree to participate in the study via interacting with the IHD by confirming weekly energy use figures to the research team submitted via IHD (this will document participant exposure to electrical costs)
- Allow the study team to collect, retain and publish <u>anonymized</u> energy use data gained through the study, and any relevant historical use data.

Of these households, a portion will be randomly selected to be in a control group to test for the potential selection bias of the opt-in group. Their aggregate usage will be collected and they will participate in qualitative interviews, but they will receive no other treatment.

The remaining households will be divided into eight sub-treatment groups and arranged in a 3-factor crossed factorial design, which stipulates that each of the eight groups will receive one level of each of three treatments, with the eight groups cumulatively representing all possible combinations of the three treatments.

The treatment factors will be as follows (combinations of treatment variables indicated in table I):

- **receive aggregate/disaggregated feedback (two levels)**
    - Aggregate groups will be given whole-home usage information; Disaggregated groups will be given appliance-level usage.
- **receive/do not receive feedback corresponding to level of real-time household usage (two levels)**
    - IHD screens will show a color-coded usage indicator at all times (automatically adjusted for ambient brightness) showing current usage in the home for those groups selected to receive real-time feedback
    - As an example of presentation, low usage could be indicated by the blue spectrum, shifting to green, yellow, orange and red for highest usage

- **Receive/do not receive weekly interactive prompts for exposure to usage in $USD**
    - IHD screens will blink white at regular intervals one evening per week in homes selected to receive weekly prompts in order to summon a resident to interact with the device
    - A resident of the home will activate the IHD and be presented with their weekly usage depending on their treatment group (aggregate or disaggregated)
    - Participants will slide an icon containing usage figure(s) from one side of the screen to the other

Group	Disaggregation	Real-time Feedback	Weekly Prompts
1	Aggregate	No	No
2	Aggregate	No	Ye$
3	Aggregate	Yes	No
4	Aggregate	Yes	Ye$
5	Disaggregated	No	No
6	Disaggregated	No	Ye$
7	Disaggregated	Yes	No
8	Disaggregated	Yes	Ye$

Table I: Summary of treatment groups proposed in study design.

All households within treatment groups will be outfitted with DEU monitoring equipment and an IHD. Participants will have constant access to their historical and real-time usage data (aggregate or disaggregated, depending on participant group), and their interactions with the IHD will be logged. The eight sub-treatment groups, each (ideally) containing participant households, will be differentiated only by the behavior of the IHD as it corresponds to their treatment group. For example, while treatment group 1 will have access to their aggregate usage, they will receive no prompts and no real-time feedback. Group 3 will have access to aggregate usage and receive real-time usage feedback, but will receive no weekly prompts. Group 4 will receive aggregate usage information, real-time feedback and weekly prompts. Group 8 will have access to disaggregated, appliance-level usage, receive real-time feedback, and receive weekly prompts.

Participant households will be observed, and data will be collected for at least one year. At the study's completion data will be analyzed to establish the effects of each level of treatment, and tested for interaction, by running multiple regression and analysis of variance (ANOVA), to find the main effect of each of the three treatments on reduction in electricity usage, and all interaction effects between treatments. Control variables will include income, geography, family size, and previous usage history.

Study Considerations

Adding, Subtracting, or Modifying Factors or Levels

- Factors may be added (or subtracted) depending upon prerogative of researchers and feasibility
- an increase in factors or levels may necessitate a larger study group, whereas a smaller sample size may be adequate if factors are reduced.

- Researchers may choose to test and include other variables, including energy awareness, appliance efficiency, home size, urban/rural, renter/homeowner, etc.

Electricity Pricing

- At a minimum, researchers must customize IHDs with respect to electricity cost by inputting real electricity prices to provide participant households with real dollar-cost information.
- IHD should integrate with dynamic pricing schemes in jurisdictions where they are available, reflecting those real consumer prices.
- Integration with dynamic pricing is also advisable to gather price elasticity and behavioral data on households subject to changing prices.
- In jurisdictions where real-time pricing is available (as opposed to scheduled time-of-use pricing), researchers may be given experimental control of those prices, in order to establish a *data-based* cost curve for household electricity use; this type of study may require a substantially larger sample size.

Participation

- As indicated in previous studies, some level of attrition is likely (Vine et al. 2014, 630) – there may be drop-off in participation as the study progresses.

- Researchers should be cognizant of the potential for greater drop-off among groups experiencing more intrusive treatments.
- Researchers should consider the possibility of the introduction of bias due to self-selection of participants who do not complete the study.
- Keeping participants engaged may require intervention, however care should be taken not to influence potential results.

Testing Sustained Results

- After the study completion, researchers may remove some IHDs to study the degree to which any behavioral changes persist or regress.
- The study (or some portion of it) may be continued beyond the initial study period.

High-Use Households, Income, and Other Participant Characteristics

- Researchers should use historical usage not only as a baseline for future usage behavior, but also as a variable within regressions to analyze differences in usage change and prior usage.
- Researchers should collect comprehensive demographic and household information to control for and examine effects of income, household size, and other characteristics to control for baseline usage and to allow investigation into correlations between those characteristics responsiveness to various feedback methods.

- Researchers should consider the option to block participant households by low- and high-usage, to obtain representative samples within each sub-treatment group

The general hypothesis for the study is that households will modify their energy use when they are provided with regular and incremental access to detailed information about the actual costs of their household energy use decisions.

The Role of a Pilot and Considerations for a Wider Study

A pilot for this study involving implementation of the design using several homes will act as a "proof-of-concept" on the feasibility of the wider study. A pilot will provide fundamental insights on potential changes in design features of the larger study, and will highlight potential implementation and management challenges, as well as offer a means to "beta test" technology and data management for researchers.

1. <u>Controlled, randomized study is stressed in the literature; collaboration with electricity provider is likely necessary</u>

Since consent is of course necessary, achieving randomization in household energy studies remains a significant, if unattainable challenge. Large studies in the field are criticized for this reason, and it is possible that only through close cooperation with an electricity provider could true randomization be achieved.

Additionally, an electricity provider may be well-positioned to aid in a more comprehensive study, since their access to household energy could provide valuable baseline information which would reduce concerns about bias coming from large-scale changes in behavior influenced by economic or weather factors.

2. <u>Simplicity of the interface, ease of installation, and efficiency in collecting data is essential</u>

While a pilot study in which several households are monitored may be executed via email, or even pen and paper, a larger study presents resource constraints, and a seamless, efficient method of managing large volumes of data must be established. Ideally this could be achieved with only slight modifications of existing software associated with the device, however it is possible that design of a data collection interface may be necessary.

3. <u>A pilot study will provide useful information on the hardware, implementation, and personnel costs of a larger study</u>

The pilot study will serve to address study design flaws and technical considerations and will inform researchers not only about the basic efficacy of a larger study, but also what resources may be necessary to manage a larger study, including needs to interact with participants, manage equipment and install issues, and other administrative duties. The pilot will allow for adequate assessment of personnel needs for the larger study. It will also inform cost calculations and the limitations posed by funding for the larger study.

CHAPTER 15: CONCLUSIONS

New technology, the evolution of energy sources, and the imperative to address climate change are all contributing to a changing electrical grid. Along with these changes, it is important that policymakers should be motivated to encourage and incentivize reductions in electricity use where possible, and to move households away from usage patterns that unnecessarily rely upon dirtier and more expensive electricity production. In that sense, we are presented with an opportunity to move toward policies that seek greater engagement with the many end-users of electricity. The behavioral changes necessary to reduce and shift energy use begin with a greater individual understanding of our behaviors and their impacts.

Research into consumer awareness and energy use has contributed to significant advances in our knowledge of our consumption behavior, and has led to interventions that have already begun to show real savings by consumers. But researchers should include in their focus those individual behaviors that are the source of our energy use, and policymakers must make greater efforts in enacting policies that connect energy users to the real costs of their use.

There is a substantial body of research investigating the ability of various utility use feedback methods to affect household electricity usage. Disaggregated electricity use feedback has a potential role in influencing households to reduce electricity use, and current technologies offer both study and population-wide potential for DEU feedback. Technical challenges of previous studies have limited the abilities of researchers to adequately evaluate the potential for DEU feedback to influence household consumption behavior. These studies have historically faced the choice of researching consumer response to idealized usage regimes, or evaluating and comparing existing systems which may present various forms of feedback in unequal ways. But we are approaching a technological horizon in electricity feedback, where questions of both consumer response and system effectiveness may be tested simultaneously.

A study using newly available technology may provide answers to questions that have plagued researchers for decades. But some study concerns remain insurmountable, including selection bias issues and privacy concerns that will continue to limit the robustness of study findings. Additionally, demand management programs rely on cost effectiveness for implementation, so although scalable technologies exist, which will likely influence improved savings among participating households. Whether a proposed project involving DEU feedback offers a cost-effective intervention will remain a question answered by current markets and project costs.

But there is substantial potential to inform approaches at targeted sub-groups – those disproportionately high consumers of electricity, and income and demographic groups that may prove more responsive to certain types of feedback (Sexton 2015). Usage patterns across homes have shown to have wide variance (Gram-Hanssen 2013, 451; Armel et al. 2013; Lutzenhiser 2014, 146; Murtagh, Gatersleben, and Uzzell 2014). It is possible that higher-use homes offer larger potential percentage reductions, and because percentage reductions for these homes are larger in absolute terms. These higher potential yields of savings from high-use homes may be cost-effective even if a wider roll-out is not. Additionally, a study testing various factors can inform the relative advantages of customization or tailoring of studies to various groups to obtain larger impacts. Finally, reliable estimates of longer-term savings associated with various feedback regimes may aid planners and policymakers as they approach the hardware standards of future homes – which types of available feedback methods should be standardized across populations in efforts to reduce demand or influence usage patterns.

The policy implications of a study like the one proposed herein will be significant. Whether such a study reveals new and cost-effective tools for electricity management, or suggests that DEU feedback offers limited advantages over simpler and less expensive interventions, such a study, if properly executed, may provide definitive findings of the relative efficacy of various electricity feedback interventions.

APPENDIX: CONSUMER ELECTRICITY AWARENESS SPECTRUM

It may be useful to consider consumer awareness of electricity usage and cost as existing on a spectrum. A framework for such a spectrum is sketched below, from lowest awareness and no exposure to cost, to highest awareness and exposure. These different levels correspond somewhat to consumption patterns. We can envision a usage and expenditure curve associated with these various levels that is non-linear. If we can arrive at realistic usage characteristics associated with each of these levels, we may offer policymakers a tool with which they can more adequately assess the costs and benefits associated with interventions that move households along the awareness spectrum.

Lowest awareness**:**

- Bill is paid by another party (landlord, homeowner association)
- actual bill cost is not known
- No thought/comprehension of electrical costs
- No feedback regarding household electrical use

Very low awareness**:**

- Electrical use is paid monthly by another party, or paid via automatic withdrawal, and rarely discussed
- No concept of which behaviors/appliances are electricity-intensive
- No thought/comprehension of electrical costs

- No feedback regarding household electrical use

Low awareness**:**

- Bill may or may not be paid by consumer
- consumer knows monthly household electricity cost
- bill is not understood beyond the bottom line price
- Little concept of which behaviors/appliances are electricity-intensive
- Little thought/comprehension of electrical costs
- No feedback regarding household electrical use

Medium awareness**:**

- Bill is paid by consumer and/or occasionally discussed in the home
- electrical units (kWh/joules) are roughly understood in terms of usage
- Some understanding electrical costs associated with various types of home use
- Some thought/comprehension of electrical costs
- No feedback regarding household electricity use

Medium-High awareness**:**

- Electrical use is paid by consumer and regularly discussed among household members;
- Electricity bill is understood in terms of units

- Good knowledge of relative electrical costs associated with various types of appliance use - consumer can make rough estimates of appliance-level usage costs
- Good comprehension and regular thought of electrical costs
- No feedback of household-level or appliance level electricity use

High awareness**:**

- Good comprehension and regular thought of electrical costs
- Electrical use is paid by consumer and regularly discussed in the home
- Bill is well-understood in terms of units
- Good knowledge of relative electrical costs associated with various types of home use consumer can make rough estimates of appliance-level usage costs
- **Some exposure to real-time feedback of household-level electricity costs**

Very high awareness**:**

- Good comprehension and daily exposure to electrical costs
- Electrical use is paid by consumer and regularly discussed in the home; some household members are actively engaged in electricity conservation
- Good knowledge of electrical costs associated with all types of home use

- Good knowledge of appliance-level usage costs: can roughly identify electrical cost-per-hour of appliances
- Daily exposure to real-time feedback of household-level electricity costs; exposure to daily/weekly/monthly assessments
- **Daily/weekly exposure to appliance-level electricity costs**

Highest awareness

- Good comprehension and daily exposure to electrical costs
- Electrical use is paid by consumer and regularly discussed in the home; some household members are actively engaged in electricity conservation
- Very high knowledge of electrical costs associated with all types of home use
- Near-perfect knowledge of appliance-level usage costs: can reliably identify cost-per-hour for appliances
- Multiple times-per-day exposure to real-time feedback of household-level electricity costs
- **Regular (daily or more) exposure to appliance-level electricity costs**
- **Engagement of appliance-level use assessments multiple times per month**

With an understanding of the many levels of electricity use awareness, and a baseline of analysis of the existing literature, we can imagine an "awareness curve" of electricity use, likely starting with high and inefficient use at the "lowest awareness" level, and gaining efficiency at the higher levels. A study of regular exposure and disaggregation will inform us what that curve looks like between the "high" and "highest" levels of granularity and regular, dollar-amount exposure to electricity costs.

There is some evidence of household usage differences at these various levels, as discussed in our survey of previous studies. But a comparison of those studies is fraught with concerns.

While there are concerns within individual studies about unequal treatment groups as in the PG&E study (Nexant 2014), a comparison of results across studies is doubly challenging. The many studies in electricity feedback have used different interfaces and methods of transmitting usage information, from monthly mailings, to many different forms of disaggregated or whole-home usage feedback. Perhaps the largest constraint is itself technological, since changes in technical capabilities have been significant in the past several years, and have changed drastically over the several decades since formal study of feedback and disaggregation began. Thus, the systematic analyses and comparison of results across studies of these different levels of awareness are constrained in their broad predictive ability.

Again, the ineffectiveness of previous studies and meta-analyses in this area begs for study of these various awareness levels *on a common platform*. Such a platform that could differentiate treatment groups only by the methods of delivering usage information could virtually eliminate concerns about interface, varying study design, etc.

It should also be noted, that if the study is well-executed, findings are highly relevant whether-or not we observe a substantial behavioral change between these higher levels – if we find that frequent exposure to granular electricity costs offer little or no efficiency over occasional exposure to home-level electricity costs, that sets an important benchmark for the design of future electricity efficiency interventions.

BIBLIOGRAPHY

Ahmadi-Karvigh, Simin, Burcin Becerik-Gerber, and Lucio Soibelman. 2016. "A Framework for Allocating Personalized Appliance-Level Disaggregated Electricity Consumption to Daily Activities." *Energy and Buildings* 111 (January): 337–50. doi:10.1016/j.enbuild.2015.11.029.

Allcott, Hunt. 2011. "Social Norms and Energy Conservation." *Journal of Public Economics* 95 (9): 1082–95. doi:10.1016/j.jpubeco.2011.03.003.

Allcott, Hunt, and Todd Rogers. 2014. "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation." *The American Economic Review* 104 (10): 3003–37. doi:10.1257/aer.104.10.3003.

Allen, Summer, Thomas Dietz, and Aaron M. McCright. 2015. "Measuring Household Energy Efficiency Behaviors with Attention to Behavioral Plasticity in the United States." *Energy Research & Social Science* 10 (Journal Article): 133–40. doi:10.1016/j.erss.2015.07.014.

Armel, Carrie K., Abhay Gupta, Gireesh Shrimali, and Adrian Albert. 2013. "Is Disaggregation the Holy Grail of Energy Efficiency? The Case of Electricity." *Special Section: Transition Pathways to a Low Carbon Economy* 52 (January): 213–34. doi:10.1016/j.enpol.2012.08.062.

Asadinejad, Ailin, and Kevin Tomsovic. 2017. "Optimal Use of Incentive and Price Based Demand Response to Reduce Costs and Price Volatility." *Electric Power Systems Research* 144 (Journal Article): 215–23. doi:10.1016/j.epsr.2016.12.012.

Bartram, Lyn. 2015. "Design Challenges and Opportunities for Eco-Feedback in the Home." *IEEE Computer Graphics and Applications* 35 (4): 52–62. doi:10.1109/MCG.2015.69.

Bartram, Lyn. 2016. "Personal Energy Analytics: Successes, Failures and Challenges." NILM Workshop 2016, Vancouver, BC, May 15. https://www.youtube.com/playlist?list=PLg1ui6mkjJfv_k-FeHh2hNp0IhRwiTmCj.

Berns, Gregory S., David Laibson, and George Loewenstein. 2007. "Intertemporal Choice – toward an Integrative Framework." *Trends in Cognitive Sciences* 11 (11): 482–88. doi:10.1016/j.tics.2007.08.011.

Bernstein, Mark, and Myles Collins. 2014. "SAVING ENERGY THROUGH BETTER INFORMATION: A NEW ENERGY PARADIGM?" *Contemporary Economic Policy* 32 (1): 219–29. doi:10.1111/j.1465-7287.2012.00330.x.

Bonino, Dario, Fulvio Corno, and Luigi De Russis. 2012. "Home Energy Consumption Feedback: A User Survey." *Energy & Buildings* 47 (Journal Article): 383–93. doi:10.1016/j.enbuild.2011.12.017.

Boonekamp, Piet G.M. 2007. "Price Elasticities, Policy Measures and Actual Developments in Household Energy Consumption – A Bottom up Analysis for the Netherlands.” *Energy Economics* 29 (2): 133–57. doi:10.1016/j.eneco.2005.09.010.

Boudet, Hilary S., June A. Flora, and K. Carrie Armel. 2016. “Clustering Household Energy-Saving Behaviours by Behavioural Attribute.” *Energy Policy* 92 (May): 444–54. doi:10.1016/j.enpol.2016.02.033.

Buchanan, Kathryn, Riccardo Russo, and Ben Anderson. 2014. “Feeding Back about Eco-Feedback: How Do Consumers Use and Respond to Energy Monitors?” *Energy Policy* 73 (October): 138–46. doi:10.1016/j.enpol.2014.05.008.

Carlson, Derrick R., H. Scott Matthews, and Mario Bergés. 2013. “One Size Does Not Fit All: Averaged Data on Household Electricity Is Inadequate for Residential Energy Policy and Decisions.” *Energy and Buildings* 64 (Journal Article): 132–44. doi:10.1016/j.enbuild.2013.04.005.

Fan, Shu, and Rob J. Hyndman. 2011. “The Price Elasticity of Electricity Demand in South Australia.” *Energy Policy* 39 (6): 3709–19. doi:10.1016/j.enpol.2011.03.080.

Faruqui, Ahmad, and Sanem Sergici. 2010. “Household Response to Dynamic Pricing of Electricity: A Survey of 15 Experiments.” *Journal of Regulatory Economics* 38 (2): 193–225. doi:10.1007/s11149-010-9127-y.

Faruqui, Ahmad, Sanem Sergici, and Ahmed Sharif. 2010. “The Impact of Informational Feedback on Energy consumption—A Survey of the Experimental Evidence.” *Energy* 35 (4): 1598–1608. doi:10.1016/j.energy.2009.07.042.

Faustine, Anthony, Nerey Henry Mvungi, Shubi Kaijage, and Kisangiri Michael. 2017. “A Survey on Non-Intrusive Load Monitoring Methodies and Techniques for Energy Disaggregation Problem,” Dept. of Communication Science and Engineering, NM-AIST, Tanzania Working Paper. https://arxiv.org/pdf/1703.00785.pdf

Fischer, Corinna. 2008. “Feedback on Household Electricity Consumption: A Tool for Saving Energy?” *Energy Efficiency* 1 (1): 79–104. doi:10.1007/s12053-008-9009-7.

Gardner, Gerald T., and Paul C. Stern. 2008. “The Short List: The Most Effective Actions U.S. Households Can Take to Curb Climate Change.” *Environment: Science and Policy for Sustainable Development* 50 (5): 12–25. doi:10.3200/ENVT.50.5.12-25.

Gram-Hanssen, Kirsten. 2013. “Efficient Technologies or User Behaviour, Which Is the More Important When Reducing Households’ Energy Consumption?” *Energy Efficiency* 6 (3): 447–57. doi:10.1007/s12053-012-9184-4.

Greer, Monica. 2012. *Electricity Marginal Cost Pricing: Applications in Eliciting Demand Responses*. Book, Whole. Amsterdam;Boston; Science Direct. http://www.sciencedirect.com/science/book/9780123851345

Hargreaves, Tom, Michael Nye, and Jacquelin Burgess. 2013. “Keeping Energy Visible? Exploring How Householders Interact with Feedback from Smart

Energy Monitors in the Longer Term.” *Energy Policy* 52 (1): 126–34. doi:10.1016/j.enpol.2012.03.027.

Hart, G. W. 1992. “Nonintrusive Appliance Load Monitoring.” *Proceedings of the IEEE* 80 (12): 1870–91. doi:10.1109/5.192069.

Hayes, S. C., and J. D. Cone. 1977. “Reducing Residential Electrical Energy Use: Payments, Information, and Feedback.” *Journal of Applied Behavior Analysis* 10 (3): 425.

Hosgor, Enes. 2015. “Taking the ‘Pulse’ of Your Home or Office’s Electric Load.” *Rocky Mountain Institute*, June 8. http://blog.rmi.org/blog_2015_06_08_taking_the_pulse_of_your_home_or_offices_electric_load.

Howard, Jacqueline. 2015. “Here’s What The Future Of Energy Might Look Like. And It’s Pretty Amazing.” *Huffington Post*, July 7. http://www.huffingtonpost.com/2015/07/07/future-of-energy-video_n_7410468.html.

Jacobsen, Grant D. 2015. “Do Energy Prices Influence Investment in Energy Efficiency? Evidence from Energy Star Appliances.” *Journal of Environmental Economics and Management* 74 (November): 94–106. doi:10.1016/j.jeem.2015.09.004.

Jain, Rishee K., John E. Taylor, and Patricia J. Culligan. 2013. “Investigating the Impact Eco-Feedback Information Representation Has on Building Occupant Energy Consumption Behavior and Savings.” *Energy and Buildings* 64 (Journal Article): 408–14. doi:10.1016/j.enbuild.2013.05.011.

Jain, Rishee K., John E. Taylor, and Gabriel Peschiera. 2012. “Assessing Eco-Feedback Interface Usage and Design to Drive Energy Efficiency in Buildings.” *Energy and Buildings* 48 (May): 8–17. doi:10.1016/j.enbuild.2011.12.033.

Janko, Samantha A., Michael R. Arnold, and Nathan G. Johnson. 2016. “Implications of High-Penetration Renewables for Ratepayers and Utilities in the Residential Solar Photovoltaic (PV) Market.” *Applied Energy* 180 (Journal Article): 37–51. doi:10.1016/j.apenergy.2016.07.041.

John Dobson, and Anthony Griffin. 1992. “Conservation Effect of Immediate Electricity Cost Feedback on Residential Consumption Behavior.” Proceedings: Summer Study on Energy Efficiency in Buildings. http://aceee.org/files/proceedings/1992/data/papers/SS92_Panel10_Paper06.pdf.

Kelly, Jack, and William Knottenbelt. 2016. “Does Disaggregated Electricity Feedback Reduce Domestic Electricity Consumption? A Systematic Review of the Literature,” Delivered at the 3rd International NILM Workshop, Vancouver, May 2016 https://arxiv.org/pdf/1605.00962.pdf

Khatib, Hisham. 2014. *Economic Evaluation of Projects in the Electricity Supply Industry*. Vol. 3rd. Book, Whole. Stevenage: IET. http://digital-library.theiet.org.ezproxy.library.tufts.edu/content/books/po/pbpo070e.

Labandeira, Xavier, José M. Labeaga, and Xiral López-Otero. 2012. "Estimation of Elasticity Price of Electricity with Incomplete Information." *Energy Economics* 34 (3): 627–33. doi:10.1016/j.eneco.2011.03.008.

Lossin, Felix, Allister Loder, and Thorsten Staake. 2016. "Energy Informatics for Behavioral Change: Increasing the Participation Rate in an IT-Based Energy Conservation Campaign Using Social Norms and Incentives." *Computer Science - Research and Development* 31 (3): 149–55. doi:10.1007/s00450-014-0295-3.

Lutzenhiser, Loren. 2014. "Through the Energy Efficiency Looking Glass." *Energy Research & Social Science* 1 (March): 141–51. doi:10.1016/j.erss.2014.03.011.

McCarney, Rob, James Warner, Steve Iliffe, Robbert van Haselen, Mark Griffin, and Peter Fisher. 2007. "The Hawthorne Effect: A Randomised, Controlled Trial." *BMC Medical Research Methodology* 7 (1): 7–30. doi:10.1186/1471-2288-7-30.

McCollough, John. 2010. "Consumer Discount Rates and the Decision to Repair or Replace a Durable Product: A Sustainable Consumption Issue." *Journal of Economic Issues* 44 (1): 183–204.

McKerracher, Colin, and Jacopo Torriti. 2013. "Energy Consumption Feedback in Perspective: Integrating Australian Data to Meta-Analyses on in-Home Displays." *Energy Efficiency* 6 (2): 387–405. doi:10.1007/s12053-012-9169-3.

Midden, Cees J.H., Joanne F. Meter, Mieneke H. Weenig, and Henk J.A. Zieverink. 1983. "Using Feedback, Reinforcement and Information to Reduce Energy Consumption in Households: A Field-Experiment." *Journal of Economic Psychology* 3 (1): 65–86. doi:10.1016/0167-4870(83)90058-2.

Min, Jihoon, Inês L. Azevedo, Jeremy Michalek, and Wändi Bruine de Bruin. 2014. "Labeling Energy Cost on Light Bulbs Lowers Implicit Discount Rates." *Ecological Economics* 97 (January): 42–50. doi:10.1016/j.ecolecon.2013.10.015.

Molina, Maggie. 2014. "The Best Value for America's Energy Dollar: A National Review of the Cost of Utility Energy Efficiency Programs." Research Report. American Council for an Energy Efficient Economy. http://aceee.org/research-report/u1402

Murtagh, Niamh, Birgitta Gatersleben, and David Uzzell. 2014. "20:60:20 - Differences in Energy Behaviour and Conservation between and within Households with Electricity Monitors: e92019." *PLoS One* 9 (3). doi:10.1371/journal.pone.0092019.

Neenan, B.F., and J. Robinson. 2010. "Guidelines for Designing Effective Energy Information Feedback Pilots: Research Protocols." Electric Power Research Institute, Palo Alto, CA. https://www.smartgrid.gov/files/EPRI.pdf.

Nexant. 2014. “HAN Phase 3 Impact and Process Evaluation Report.” http://www.myaztech.ca/wp-content/uploads/PGE-HAN_Impacts_and_Savings_Report_FINAL.pdf.
Nyquist, Scott. 2016. “Energy 2050: Insights from the Ground up.” Article. McKinsey and Co. http://www.mckinsey.com/industries/oil-and-gas/our-insights/energy-2050-insights-from-the-ground-up.
P3 International. 2017. “‘Kill-a-Watt’ Description Page.” P3 International, Website. http://www.p3international.com/products/p4400.html.
Rodgers, J., and L. Bartram. 2011. “Exploring Ambient and Artistic Visualization for Residential Energy Use Feedback.” *IEEE Transactions on Visualization and Computer Graphics* 17 (12): 2489–97. doi:10.1109/TVCG.2011.196.
Rowlands, Ian H., Tobi Reid, and Paul Parker. 2015. “Research with Disaggregated Electricity End-use Data in Households: Review and Recommendations.” *Wiley Interdisciplinary Reviews: Energy and Environment* 4 (5): 383–96. doi:10.1002/wene.151.
Schultz, P. Wesley, Mica Estrada, Joseph Schmitt, Rebecca Sokoloski, and Nilmini Silva-Send. 2015. “Using in-Home Displays to Provide Smart Meter Feedback about Household Electricity Consumption: A Randomized Control Trial Comparing Kilowatts, Cost, and Social Norms.” *Energy* 90, Part 1 (October): 351–58. doi:10.1016/j.energy.2015.06.130.
Schwartz, Daniel, Baruch Fischhoff, Tamar Krishnamurti, and Fallaw Sowell. 2013. “The Hawthorne Effect and Energy Awareness.” *Proceedings of the National Academy of Sciences* 110 (38): 15242–46. doi:10.1073/pnas.1301687110.
Schwartz, T., G. Stevens, T. Jakobi, S. Denef, L. Ramirez, V. Wulf, and D. Randall. 2015. “What People Do with Consumption Feedback: A Long-Term Living Lab Study of a Home Energy Management System.” *INTERACTING WITH COMPUTERS* 27 (6): 551–76. doi:10.1093/iwc/iwu009.
Sexton, Steven. 2015. “Automatic Bill Payment and Salience Effects: Evidence from Electricity Consumption.” *REVIEW OF ECONOMICS AND STATISTICS* 97 (2): 229–41. doi:10.1162/REST_a_00465.
Southwell, Brian, Jan DeWaters, Joseph Murphy, and Patricia LeBaron. 2012. “Americans’ Perceived and Actual Understanding of Energy.” RTI Press. https://www.rti.org/sites/default/files/resources/rr-0018-1208-southwell.pdf.
Sundramoorthy, V., G. Cooper, N. Linge, and Qi Liu. 2011. “Domesticating Energy-Monitoring Systems: Challenges and Design Concerns.” *IEEE Pervasive Computing* 10 (1): 20–27. doi:10.1109/MPRV.2010.73.
Talbot, David. 2016. “Find Out Which Appliance Is Sucking All Your Power.” *MIT Technology Review*, July 13. https://www.technologyreview.com/s/601881/find-out-which-appliance-is-sucking-all-your-power/.
Torriti, Jacopo, Richard Hanna, Ben Anderson, Godwin Yeboah, and Angela Druckman. 2015. “Peak Residential Electricity Demand and Social

Practices: Deriving Flexibility and Greenhouse Gas Intensities from Time Use and Locational Data." *Indoor and Built Environment* 24 (7): 891–912. doi:10.1177/1420326X15600776.

US EIA. 2011. "US EIA Annual Energy Review 2011." US Energy Information Administration. https://www.eia.gov/totalenergy/data/annual/pdf/aer.pdf.

US EIA 2017. "US Energy Information Administration Monthly Report." https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf.

US EPA. 2017. "US EPA Electricity Consumption by Sector 2014." https://www.epa.gov/energy/electricity-customers.

US EPA 2017. "US Environmental Protection Agency - Climate Change: Basic Information." Accessed March 30. https://www.epa.gov/climatechange/climate-change-basic-information.

Vassileva, Iana, Monica Odlare, Fredrik Wallin, and Erik Dahlquist. 2012. "The Impact of Consumers' Feedback Preferences on Domestic Electricity Consumption." *(1) Green Energy; (2)Special Section from Papers Presented at the 2nd International Energy 2030 Conf* 93 (May): 575–82. doi:10.1016/j.apenergy.2011.12.067.

Vine, Edward, Michael Sullivan, Loren Lutzenhiser, Carl Blumstein, and Bill Miller. 2014. "Experimentation and the Evaluation of Energy Efficiency Programs." *Energy Efficiency* 7 (4): 627–40. doi:10.1007/s12053-013-9244-4.

Weliczko, Erika. 2013. "Tracking Your Energy Use with Home Monitoring Systems." *Homepower*, February/March, Issue 153. https://www.homepower.com/articles/home-efficiency/electricity/tracking-your-energy-use.

Westskog, H., T. Winther, and H. Saele. 2015. "The Effects of In-Home Displays-Revisiting the Context." *SUSTAINABILITY* 7 (5): 5431–51. doi:10.3390/su7055431.