Goal Setting and Energy Efficiency*

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Abstract

This paper shows that non-binding, personal goal setting can act as an effective mechanism to induce energy efficiency and conservation actions in the residential sector. We evaluate a large-scale implementation of an energy efficiency program in Northern Illinois and conclude that, on average, households saved approximately 4.4%. However, savings are heterogeneous, and consumers choosing realistic goals persistently save substantially more than those choosing very low goals or unrealistically high goals. We develop and find support for a theoretical model of present-biased consumers with reference-dependent preferences that identifies the behavioral mechanism through which goals impact consumption in the data.

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1 Introduction

As the impact of climate change has become increasingly stark, policymakers have renewed interest in implementing interventions that can improve energy efficiency. In light of general federal inaction on implementing price-based interventions such as introducing a carbon tax or allowing emissions trading in the foreseeable future, economists have begun to advocate the use of behavioral "nudges," which are non-price interventions grounded in psychology and behavioral economics, as a partial solution to attenuate the impact of climate change (Allcott and Mullainathan 2010). The hope is that such approaches can generate economically meaningful energy savings at low cost, mirroring like interventions that have been documented in other areas of economics, such as microfinance and retirement savings (Bertrand, Karlan, Mullainathan, Shafir and Zinman 2010, Madrian and Shea 2001).

This paper evaluates the extent to which non-binding, personal goal setting acts as a behavioral nudge to reduce energy consumption, and proposes a theoretical model of present-biased consumers with reference-dependent preferences that is supported by observed behavior. It indicates that goal setting leads to substantial and persistent energy savings of 11% for informed customers who set realistic goals, and approximately 4.4% on average for all customers. This paper is unique, in that it models a precise behavioral mechanism that explains both the decision to opt into the program as well subsequent behavior once enrolled in the program, clearly identifies the channel in the data, and measures its impact quantitatively. It adds to the growing body of empirical evidence of reference-dependent preferences (Camerer, Babcock, Loewenstein and Thaler 1997, Crawford and Meng 2011, Pope and Schweitzer 2011, Card and Dahl 2011) in a new context, with endogenous and measured reference points. Moreover, to our knowledge, it is the first empirical study in which the *motivated* use of reference dependence is demonstrated, to counteract present bias. Table 1 summarizes our findings and compares them to the most plausible explanations. We also present evidence from a follow-up field experiment that we have conducted, which further separates the potential behavioral channels. Leading alternative mechanisms based on standard preferences to explain the observed savings and sign-up patterns, such as information-seeking, are not supported by the observed results.

First, we describe the design and implementation of a program in Northern Illinois that allows utility customers to choose energy savings goals. It also provides them with information on how to implement energy-efficiency actions to save energy, and constant feedback on their performance.

Second, we show that consumers who opt into the program achieve substantial electricity savings from choosing goals. Average savings over the year post-adoption are approximately 4.4%, but up to 8% savings are achieved in the first few months of the program. Surprisingly, we find substantial and persistent savings of nearly 11% among consumers who set realistic goals, but not among those who set very low or unrealistically high goals.

Third, we introduce a theoretical model of sign-up and post-adoption usage in the program. A consumer allocates consumption between an aggregate good and electricity, a good that yields immediate benefits but a delayed (environmental) cost. If she is present-biased, she may sign up for the program because she is aware that she will consume more electricity than she prefers ex ante. If she has reference-dependent preferences, she curbs her consumption in response to a goal, which acts as her reference point, because she derives utility directly from comparing her consumption against this goal. Thus, the consumer's present-biased preferences induce her to sign up for the goal-setting program, while her reference-dependent preferences lead her to curb her consumption in response to goals.

Fourth, we explore consumers' decisions to opt into the program and the choice of goals. We find that the program is attractive to consumers who are hyperbolic and are aware of their need for commitment to attenuate overconsumption. The choice of goals reveals substantial heterogeneity in consumers. While 73% of consumers choose realistic or optimistic goals, 15% of consumers choose the minimum goal possible. About 12% of consumers choose impossibly high goals. Consistent with our model's predictions, consumers who set realistic goals achieve persistently higher savings of about 11% on average, while other consumers save less.

We conclude by ruling out leading alternative mechanisms, such as information seeking and its effects. We also present evidence from a follow-up field experiment that we have conducted, where the different channels of information and goals are separated. This field experiment allows us to further identify goal setting as the mechanism driving savings, separately from information provision or other confounding factors.

Related Literature. This paper links three bodies of literature: (1) work that explores the effect of behavioral, non-price interventions on energy consumption, (2) the study of reference-dependent preferences, and (3) the literature on self-control.

Several studies suggest that utilities' interventions that include social comparisons to others' usage can meaningfully affect consumers' behavior (Allcott 2011, Ferraro and Price 2011, Costa and Kahn 2010). Harding and Rapson (2012) show that a utility's carbon offset program can lead to consumption reductions of 2-3% when the social cost of pollution is emphasized. Previous studies on the effects of personal goal-setting have found little effect of goals relative to energy-saving tips, but the control group specification and overall design are very unclear (Wilhite and Ling 1995, van Houwelingen and van Raaij 1989).

Kőszegi and Rabin (2006, 2009) model reference dependence by endogenizing reference point formation through rational expectations, which has been supported by experimental laboratory (Abeler, Falk, Goette and Huffman 2011, Ericson and Fuster 2011, Sprenger 2010) and field (Fehr and Goette 2007, Goette and Huffman 2007) evidence. There is also empirical evidence, though debated, that people use reference points across various domains (Camerer et al. 1997, Farber 2005, Farber 2008, Crawford and Meng 2011, Pope and Schweitzer 2011, Card and Dahl 2011). Hsiaw (forthcoming) finds that goals must be sufficiently realistic for reference-dependent agents to counteract present-biasedness. Goals has also been studied in settings involving costly effort and delayed benefits (Suvorov and van de Ven 2008, Koch and Nafziger 2011).

Intrapersonal conflict was first studied by Strotz (1956) and Schelling (1984), and more broadly developed by Ainslie (1992) and Laibson (1997). Evidence of present-biasedness has been demonstrated in a number of realms, including exercise, savings, and payday loans (DellaVigna 2009). Binding and reputational mechanisms for improving self-control are well-studied (Brocas and

Carrillo 2005, Carrillo 2005, Gul and Pesendorfer 2001, Bénabou and Tirole 2004).

2 CUB Energy Saver Program

To evaluate how goal setting affects energy savings, we analyze the first goal-based energy efficiency program implemented in the U.S. on a large scale. It was designed by Efficiency 2.0 (recently acquired by C3), a leading provider of energy efficiency programs to utilities, and was funded by the Citizens Utility Board (CUB) of Illinois.[1] The program was restricted to residential users, all of whom were customers of ComEd, a large utility. It was advertised to a limited subset of ComEd customers through direct mail and community events. As a result, program adoption is heavily concentrated in the Chicago Metropolitan Area.[2] We restrict our analysis to adopters during the first year of the program, starting with its introduction in June 2010, a period over which program implementation remained constant. The CUB Energy Saver program involves a website designed by C3, which can be accessed from the main CUB webpage. It provides an integrated user experience, separate from the utility website, with a focus on detailed information coupled with behavioral incentives.

Signing up for the program involves successfully completing three steps. First, a user must fill out basic contact information. Second, the user must provide utility account information, which allows the program to access past and future billing information. Third, the user is offered a menu of energy savings options corresponding to roughly 5%, 10% and 15% annual electricity savings, which are labeled as "No Cost," "Low Cost" and "Home Investment" plans, reflecting the extent to which a household may need to make further purchases (e.g. energy efficient appliances) to save energy. Each savings plan comes with a concrete list of energy savings recommendations, all of which the user can see *before* selecting a goal.[3] Users can add additional energy savings

[1]CUB was set up in 1983 by the Illinois General Assembly as a nonprofit, nonpartisan organisation designed to represent the interests of residential utility consumers.

[2]In the Appendix we map the geographic distribution of adopters in Northern Illinois.

[3]The information provided is, to some extent, customized to each individual user, based on rough estimates derived from a statistical model of household energy consumption and appliance saturation.

actions from a long list of possible actions, effectively selecting a goal on a continuous savings range. Each action can be customized for a household's specific technology base (for example, by entering information on exactly how many lightbulbs will be replaced with CFLs and the number of hours they will be used per day), providing a more accurate savings estimate.

Once a consumer has signed up for the website, she can easily monitor her monthly consumption, since the website obtains and displays all past monthly electricity bills directly from the utility. Most consumers log in to the website once every 2-3 months but a fraction of the consumers appears to be very involved, logging in at least once a month. The website also rewards customers with savings "points" computed by an algorithm that adjusts savings for weather and seasonality. This algorithm is not available to the user, and points are *not* based on consumption relative to self-set goals. These points can then be redeemed for coupons offering discounts at local retail establishments. However, our analysis indicates that these points are only weakly correlated to actual savings. Point redemption is also extremely low and a survey indicates that points are not a major incentive for program adoption. Thus, we believe that the unaltered billing data is the most useful information available to households in order to monitor their consumption goals.[4]

Data. To analyze this program, we combine data from different sources. C3 collects detailed information on program participants, including the time of sign-up and monthly electricity bills before and after adoption. For each consumer, we know the precise billing cycle, which typically spans days in two calendar months. We re-normalize each bill to correspond to a calendar month by assuming uniform consumption during the month. Thus, the estimated monthly bill for each consumer is constructed as the sum of the average daily consumption from two different bills. While this introduces some inevitable measurement error, it is preferable to ignoring the different billing cycles. We thus have an (unbalanced) panel dataset from January 2009 to December 2011.

Unfortunately, since the program was not run by the local utility ComEd, we do not have

[4]In the Appendix, we discuss additional design features of the program website and argue that they provide at best noisy and unreliable information not utilized by the user. We also show screenshots from the program webpage. One illustrates the page on which the user makes her goal selection and the other displays the detailed listing of past and present billing and (kWh) usage information.

access to the full database of households that would have been eligible for the program. Since we wish to understand the decision to opt into the program in addition to the effect of adoption on consumers, we construct a "control" group of customers who could have opted in but did not. While it is impossible to determine exactly who was exposed to the varied marketing campaigns surrounding this program, we can look instead at customers who would have been eligible to opt in but did not, whatever the reason may be. To do so, we purchased voter registration files for the state of Illinois from a third party provider. We selected a random stratified sample of Illinois residents to reflect the proportion of non-adopters in the zip codes where adopters reside. Both groups of households were then linked to individual-level demographics from another third party provider. Some variables, such as age and income, are estimated at the household level. We do not know the precise age of the household head, but only whether someone of a certain age resides in the household. Consequently, households where more than one family reside together will appear twice in each respective age group. In addition to basic demographic information such as age, household income, education, presence of children and household size, we also acquired additional lifestyle information, which the third party provider obtains from past subscriptions or purchasing behavior.

To identify consumers who are motivated by environmental concerns, we acquired two variables: *environmental issues* and *green living*, which have been shown by Harding and Rapson (2012) to correlate with adoption into a carbon offsetting program in California. *Environmental issues* measures whether a household has expressed interest in environmental or wildlife issues through magazine subscriptions and/or mail response. *Green living* is a variable which aims to identify households that are living environmentally friendly, by buying green household cleaning products, eating organic foods, donating funds to environmental causes, or driving hybrids. These variables were constructed without reference to the program analyzed.

We also acquired lifestyle variables that are potential indicators of self-control problems, i.e. difficulty behaving in a manner consistent with ex ante plans. Thus, we know whether the person signing up for the program is a smoker or regularly engages in lottery and casino gaming. We also know whether the consumer is or has recently made purchases of dieting and weight loss products or participates in weight loss programs. We captured two additional variables that may also be related to self-control when interpreted as conditional on income. One is a measure of loan-to-value ratio for the household, a commonly used measure of risk based on the ratio of the current mortgage relative to market values. A ratio of 80% or above typically identifies a risky borrower, so a high loan-to-value ratio, conditional on income, may indicate weaker self-control. The other financial variable we capture is whether or not the consumer has one or more retail store lines of credit (e.g. Old Navy), which does not include bank-issued credit cards.

Our sample consists of 2487 households who signed up during the first year of the program and for which we have billing and demographic information. We also have information on 9,964 households derived from the random stratified sample of households in Illinois based on available voter registrations.[5] Table 2 shows the summary statistics for our data. Adopters are likely to be younger and more educated. They are much more likely to have gone to graduate school and live in smaller households. Adopters are also more likely to express environmental interest and to be engaged in environmentally friendly actions. Turning to our potential indicators of self-control problems, dieters are more likely to participate in the program, while smokers are less likely (though not statistically significant). Households are comparable in terms of gambling. Households with one or more credit lines are, however, less likely to participate, while households with a high loan to value ratio are more likely to sign up.[6]

3 Consumption and Savings

Identification. In attempting to analyze the extent to which goal setting as implemented by this program has lead to electricity savings, we face an important technical obstacle, the lack of a valid

[5]We obtained information on 10,000 households chosen at random from the zip codes where adoption occurred, but 36 households were already registered for the program.

[6]Note that these statements are based purely on the summary statistics and do not consider the correlations between these different demographics. Later, we will turn our attention to a conditional regression analysis to refine our demographic profile for the adopters.

control group. Even if we had access to a database of ComEd clients, CUB program adopters select into the program based on observable and unobservable characteristics which vary substantially over their broad service territory. Moreover, it is unclear how to interpret the intentions of a customer who has not signed up for a program 12 months after the program start. It may be that the customer is unaware of the program, may decide to sign up later, or may never sign up for the program.

We are thus limited to using the group of households who have opted into the program to evaluate savings. To do so, we use variation in the timing of adoption in a difference-in-differences framework to identify the effect of adoption on subsequent use, while also controlling for individual and time effects (Reber 2005, Hoynes and Schanzenbach 2009, Hoynes and Schanzenbach 2011). Our identification strategy relies on the assumption that we can compare the consumption of households who opt into the program with the consumption of households who have not yet opted in, but will do so later on. For this assumption to be valid, the timing of adoption should depend solely on marketing exposure and awareness of the program, and should not be related to observable or unobservable variables which may affect the trending behavior post-adoption.[7] We provide evidence for the robustness of our results to this assumption after introducing the main savings estimates.

Savings. To estimate average individual level savings while being as flexible as possible in terms of the econometric specification, we estimate the following "event study" equation:

$$log(kWh)_{it} = \sum_{k=-\underline{m}}^{\overline{m}} \delta_k D_{it}^k + \alpha_t + \gamma_i + \varepsilon_{it} \tag{3.1}$$

where D_{it}^k are a set of indicator variables set equal to one if, in calendar month t, household i is

[7] In the Appendix we show the pattern of adoption into the program. A duration analysis of the timing of adoption using a Han and Hausman (1990) model with flexible baseline hazard and Gamma distributed unobserved heterogeneity also reveals that while the shared baseline hazard is statistically significant, neither the observed covariates nor the unobserved heterogeneity explain the timing of adoption, thus providing support for our identification assumption. Detailed results are available from the authors.

k months away from its enrollment month in the CUB program. The model also accounts for individual effects γ_i and month-year effects α_t. The underlying assumption is that, conditional on time-invariant household characteristics and aggregate month-specific shocks, all households that are k months away from enrolling in the offset program are identical (in expectation). The specification implicitly models the response as a piecewise linear function of relative time to adoption, with no restrictions on the variation or pattern of the response over time. This provides a test of our identification assumption, as we should not observe statistically significant trends pre-adoption.

We restrict the event study window such that $k \in [\underline{m}, \overline{m}]$, and normalize the coefficient of event month prior to adoption to zero.[8] We choose 12 months pre-adoption and 18 months post-adoption as the cut-off points for our event window. The relatively long post-adoption window allows us to evaluate the long run persistence of any observed behavioral change, but it prevents us from constructing a balanced panel since data after December 2011 is not available to us. We thus remain cautious in our interpretation of the estimation results for the later months, since they may also reflect compositional changes resulting from a diminishing sample size and which will be reflected by increasing confidence bounds.

In Figure 1, we present the estimated coefficients on the indicator variables in event time. Before adoption, we see no statistically significant trends. Post adoption, however, the average estimated savings are 4.4%. Households realize very impressive saving of close to 8% by the second month after sign-up, but over the next six months, average savings diminish and become statistically indistinguishable from zero. Notice, however, that the standard errors also increase over time as the sample diminishes with the length of the event window. In the Appendix, we evaluate the robustness of these savings estimates using propensity score matching to account for the potentially varying demographics of adopters over time and estimate savings ranging from 2.9% to 4.4% depending on the matching set.

[8] Periods outside the event window are estimated at the same time as the bounds for the event window, i.e. the indicator variable for period $k = \underline{m}$ captures all periods $t \leq \underline{m}$ and the indicator variable for period $k = \overline{m}$ captures all periods $t \geq \overline{m}$.

Goal Choice and Savings. Goals are implicitly set by choosing a set of actions, each implying a certain level of electricity savings, which may vary depending on property characteristics. We quantify a consumer's selected goal levels as the implied electricity savings from implementing the chosen actions over the next year as a fraction of the total electricity usage in the 12 months prior to adoption. Although users are actively encouraged to choose a goal of 5%, 10% or 15%, the actual distribution of chosen goals is continuous. Approximately 15% of the consumers choose a 0% savings goal (i.e. they choose to select no action which they plan to implement). Approximately 32% of the consumers choose a goal greater than 0% but less than 15%. We consider goals in this range, which the program deems achievable to consumers explicitly, to be "realistic." About 41% choose savings goals in the range 15% to 50%, which we consider to be over-optimistic. In a recent consulting report, McKinsey (2009) suggests that savings of about 23% may be achievable. Meier (2009) reports that following an avalanche destroying the power transmission lines in the city of Juneau, Alaska, residents reduced energy use and improved energy efficiency by as much as 30% in the following 6 weeks. This is a fairly extreme case of what consumers can achieve under dire circumstances. Thus, goals in this range entail significant lifestyle changes and are rather over-optimistic for most consumers. The remaining 12% of consumers choose undoubtedly unreasonable goals that imply savings in excess of 50% of their previous year's consumption.

Consumers have a strong propensity to overcommit by selecting too many goals. Most consumers go well beyond the three to five actions recommended on the website. The mean consumer chooses 10 action actions, and 95% of consumers choose fewer than 25 actions. The mean consumer who chooses savings in excess of 50% commits to over 20 actions. Consumers tend to prefer options which do not require substantial financial investment, instead choosing options which rely on behavioral change.[9] Low-cost or no-cost actions alone do not fully explain the degree of overconfidence observed. The median cost of implementing the savings actions is $60, reflecting the

[9]The most popular actions chosen are: Install CFLs in your lighting fixtures; Close your blinds during summer days; Wash only full loads of dishes; Use more natural lighting; Unplug your coffee maker when you're done brewing; Clean the lint trap in your dryer before every load; Use a drying rack to dry your clothes; Turn up the temperature of your thermostat during the summer; Use a microwave oven instead of your oven for cooking; Hand clean your oven instead of using the auto clean.

large selection of low-cost actions, while the mean cost is just below $1,500, indicating that some consumers commit to very expensive investment choices. In particular, consumers with savings commitments in excess of 50% of their past savings commit to mean investments of around $3000.

Returning to the event study of post-adoption consumption post-adoption, we estimate the effect of adoption separately in relation to the chosen goals. We report the mean savings for the different groups of commitments (0%, 0%-15%, 15%-50%, 50%+) in Figure 2. After adoption, consumers choosing realistic goals achieve the most substantial and persistent savings, of 13% over the first two months and nearly 11% over 18 months. In contrast, consumers choosing no goals save about 1.5% on average, while those choosing over-optimistic goals save only 1% on average. The savings achieved by consumers choosing unrealistic goals is not statistically different from zero. This pattern suggests that consumers who choose over-optimistic or unrealistic goals quickly realize that they cannot achieve the projected savings, which were not feasible to start off with, and give up.[10]

Feedback. In the CUB program, consumers receive monthly email feedback and reward points that are not directly related to their chosen goals. Rather, they depend on the consumer's consumption relative to her weather-adjusted usage in the previous year, where the adjustment algorithm is not known to the consumer. An analysis of the feedback and points awarded reveals that they are poorly correlated with consumption. Over the program's duration, all customers received between 60 and 100 points per month. The mean number of points awarded for consumers who selected goals of 0%, 0-15%, 15-50% and 50%+ were 74, 81, 78 and 76 respectively, while the program-reported mean monthly savings over the same month a year earlier were 91, 115, 90 and 78 kWh respectively. As we show in Section 5, actual savings by these groups was 1.5%, 11%, 1% and 0%, respectively. Thus, awarded points and email feedback are a very noisy and indirect signal of true savings relative to selected goals.

[10]For clarity of presentation we omit the confidence bounds, but more detailed results are available from the authors. The results show that the savings for the group of consumers choosing realistic goals are statistically significant throughout. Furthermore, the confidence bands for this group does not overlap with the estimated savings for the other groups.

This suggests that if consumers were motivated to save solely through reward points, they would quickly give up after realizing the lack of correlation between their consumption and points earned. That is, reward points do *not* act as a material incentive for consumers to achieve their chosen goals. Therefore, the choice of goal level should be irrelevant to a standard expected-utility maximizing consumer. Nonetheless, we find positive savings in the program that persistent among a subset of consumers, and we observe a clear non-monotonic relationship between goal choice and savings. In the following sections, we consider two theoretical models to explain observed behavior. We study the relationship between program adoption and goal choice to further distinguish these two models, then determine the mechanism that drives program sign-up and post-adoption consumption.

4 Theoretical Considerations

We model a consumer's enrollment decision and her subsequent behavior as a two-stage game. In the first stage, she decides whether or not to sign up for the program. In the second stage, she chooses her monthly level of electricity consumption. If she has not signed up, then she receives no goal and consumes electricity accordingly. If she has signed up, then she receives a goal, in the form of a consumption target, and consumes electricity accordingly. Derivations and proofs are collected in the Appendix.

The model has four key features: (1) the consumption problem is a constrained allocation decision between electricity and an aggregate good, (2) electricity is a good that yields immediate benefits and delayed costs, (3) the consumer is present-biased, so she tends to overconsume electricity in the absence of intervention, and (4) the consumer has reference-dependent preferences, so a goal influences her behavior by serving as a reference point. The first two assumptions describe the consumer's basic problem and the key properties of electricity, in contrast to the aggregate good. In conjunction with these two features, the third assumption generates demand for a mechanism to attenuate future consumption. The fourth assumption explains how goal provision can serve as such a mechanism, by providing the consumer with an incentive to consume less electricity. Note that present-biasedness is *not* necessary to describe the consumer's behavior in response to goals once she has signed up for the program. Rather, present-biasedness is necessary to explain why the consumer would sign up for the program in the first place—a time-consistent consumer would be able to consume less electricity without the aid of the program if that were optimal. Thus, the model explains both *how* goal-setting affects behavior, and *why* consumers demand such an intervention.

We also consider an alternative model in which the consumer is *neither* reference-dependent nor present-biased, and is driven entirely by material benefits. As a standard expected-utility maximizer, she signs up for the program to earn reward points (and perhaps to curb consumption); likewise, her post-adoption behavior is incentivized by reward points, not reference-dependent preferences. Because the expected utility model is a special case of the first model, we develop the former and then contrast their predictions.

The Consumer's Problem. In the first stage, denoted period 0, the consumer decides whether or not to sign up for the goal-setting program. If she signs up, she incurs a one-time sign-up cost ($\varepsilon \geq 0$) in period 0. We can think of this cost as the nuisance of filling out forms to sign up and link their billing records to the program, net of the sign-up bonus. She also sets her goal r for consumption in the next period, against which she will compare her actual consumption in the second stage.

In the second stage, denoted period 1, the consumer decides how much of her income m to allocate between consumption of an aggregate good y, which has a per-unit price normalized to 1, and consumption of electricity x, which has a per-unit price p. At the end of period 1, she derives utility from consuming x and y and from comparing her consumption x to her goal r. The consumer's benefits from consumption of electricity and the aggregate good are accrued in period 1 and are described by $u(x,y)$, where $u_x > 0$, $u_y > 0$, and $u_{xx} < 0,\ u_{yy} < 0$.

Consumption of electricity also leads to a future cost to the consumer, $c(x)$. For simplicity, we assume that this future cost is incurred in the period after consumption (i.e., period 2), where δ is the consumer's discount factor. We interpret this as the future (private) cost of negative environmental effects, like the future disutility that arises from breathing polluted air and drinking polluted water.[11] We assume that the marginal cost of each additional unit is positive and weakly increasing in electricity consumption: $c(0) = 0$, $c'(x) > 0$ and $c''(x) \geq 0$. In contrast, there is no future cost associated with consumption of the aggregate good y. Thus, electricity is a good whose consumption yields immediate benefits and delayed costs.

Why might a consumer want to curb her electricity use? If she is aware that she has a self-control problem and tends to overconsume electricity, she may seek a device to counteract this tendency. The consumer has quasi-hyperbolic time preferences, so for all t,

$$U^t(u_t, u_{t+1}, u_{t+2}, \ldots) = u_t + \beta \sum_{\tau=t+1}^{\infty} \delta^\tau u_\tau, \tag{4.2}$$

where $0 < \beta \leq 1$ and $0 < \delta \leq 1$ (Phelps and Pollack 1968, Laibson 1997). Thus, the consumer's period-1 discounted utility from consuming electricity and the aggregate good is $u(x,y) - \beta\delta c(x)$. However, her ex-ante, period-0 discounted utility is equivalent to that of an exponential discounter, with $\beta = 1$. Thus, when $\beta < 1$, the consumer suffers from a time-consistency problem: she always prefers to consume more electricity in the present, but prefers that she consume less in the future.

How can a goal counteract this time-consistency problem? We assume that the consumer has additively separable, reference-dependent preferences. In addition to deriving utility from absolute consumption, she derives comparison utility from comparing her electricity consumption against a reference point r, which is the consumption goal or target that she faces under the goal-setting program, at the end of period 1. The goal is set during period 0, so it is taken as given and cannot be changed by the consumer at the time she makes the allocation decision in period 1.[12] If she does not sign up for the goal-setting program, she does not have a goal against which to evaluate herself

[11] Alternatively, we could interpret this long-term cost as her altruistic concern for the future social costs of the environment. Here, "environmental concern" can be interpreted as an individual's subjective beliefs about the discounted environmental costs from electricity usage, $\delta c(x)$.

[12] The qualitative results would be weakened but still hold if the consumer were allowed to adjust his goal in the second stage, as long as the original goal from the first stage is somewhat "sticky."

in period 1. There is extensive evidence that without a well-defined basis against which to make a comparison, vague goals have no effect on motivation and effort (Latham and Locke 1991, Mento, Locke and Klein 1992). In this case, we assume that her comparison utility equals zero.

Let the consumer's comparison utility be described by the function $f(r-x)$. The consumer derives no comparison utility from meeting her goal exactly, since she experiences neither a gain or a loss ($f(0) = 0$). She experiences positive comparison utility (i.e., a gain) when she consumes less electricity than her goal ($f(r-x) > 0$ if $r > x$). Likewise, she experiences a loss when she consumes more than her goal ($f(r-x) < 0$ if $r < x$). The function f is strictly increasing in the gap between the goal and consumption ($f'(r-x) > 0\ \forall x$). Consistent with prospect theory (Kahneman and Tversky 1979), she exhibits diminishing sensitivity to both gains and losses ($f''(r-x) < 0$ if $r > x$ and $f''(r-x) > 0$ if $r < x$).

The consumer derives utility $g(x_0 - x)$ from reward points. In contrast to comparison utility, points are awarded by the program when the consumer consumes less electricity relative to *last year's consumption in the corresponding period*, denoted x_0, rather than the self-set goal r. Clearly, past consumption must be taken as given by the consumer and cannot be changed in the second stage, and she derives no utility from having no points ($g(0) = 0$). The number of awarded points increases with the amount of electricity saved relative to x_0, but points are not subtracted when the consumer consumes *more* electricity than she did in the corresponding period last year ($g(x_0 - x) > 0$ if $x_0 > x$, $g(x_0 - x) = 0$ if $x_0 \leq x$). Receiving more points yields more, but diminishing marginal, utility ($g'(x_0 - x) > 0$ and $g''(x_0 - x) < 0$ if $x_0 > x$, and $g'(x_0 - x) = g''(x_0 - x) = 0$ if $x \leq x$).

Thus, the consumer's problem in period 1 is

$$\max_{x,y} u(x,y) + 1_{signup}[f(r-x) + g(x_0 - x)] - \beta\delta c(x) \quad \text{subject to } m \geq px + y, \tag{4.3}$$

where $1_{signup} = 1$ if the consumer has signed up for the program and is zero otherwise. When deciding whether to sign up for the program in period 0, she takes into account her consumption behavior in response to the goal and the reward points she would earn.[13]

[13] In the Appendix, we account for period-1 costs of implementing goals in the model, for which qualitative results

Characterizing Consumer Behavior. Let (x^*, y^*) be the consumer's consumption if she signs up for the program. When $\beta < 1$, the consumer is present-biased, undervaluing the future costs of electricity consumption relative to its immediate benefits. This leads her to consume more electricity than she prefers from an ex-ante perspective, when she would like to consume as though $\beta = 1$. The presence of a consumption goal r counteracts this tendency, because she is motivated to increase comparison utility by consuming less. When the goal is achievable ($r \geq x$), a more ambitious goal motivates her to consume less due to diminishing sensitivity to gains - the marginal gain from decreasing consumption is higher as r decreases in the gains region. But, because the consumer exhibits diminishing sensitivity to losses, a goal that is excessively ambitious ($r < x$) becomes *less* effective as it becomes even more ambitious - the marginal gain from decreasing consumption is lower as r decreases in the loss region. As long as the consumer cares about future utility ($\beta > 0$), she will decrease electricity usage as its discounted costs increase.

Proposition 1 *Given a consumption goal r, the consumer's electricity usage upon sign-up has the following properties:*

1. *Her usage increases with present-biasedness:* $\frac{\partial x^*}{\partial \beta} < 0$.
2. *When her consumption is lower than her goal, her usage decreases as her consumption goal decreases:* $\frac{\partial x^*}{\partial r} > 0$ *when* $r \geq x^*$. *When her consumption is higher than her goal, her usage increases as her consumption goal decreases:* $\frac{\partial x^*}{\partial r} < 0$ *when* $r < x^*$.
3. *Her usage decreases as the discounted environment cost increases:* $\frac{\partial x^*}{\partial \delta} < 0$ *when* $\beta > 0$.

In period 0, the consumer decides whether to sign up for the program, and sets a goal for the second stage if he does so. If she signs up, she incurs a one-time sign-up cost, denoted $\varepsilon \geq 0$. Thus, the sign-up decision has an initial fixed cost (ε), and a delayed period-1 benefit that arises from consuming a level of electricity closer to the customer's ex-ante optimum.

are unchanged.

At this point, the manner in which the goal is determined is crucial for the sign-up decision and characterizing subsequent behavior. We assume that the selected goal must be fully consistent with the consumer's beliefs about the outcome she will achieve. That is, she must set a goal that she believes she will actually meet, satisfying rational expectations. Under the interpretation that the the goal acts as a reference point against which the consumer compares her consumption, this assumption is consistent with psychological findings, as well as prevailing theoretical work on reference-dependent preferences. Based on lab and field experiments, Latham and Locke (1991) conclude that goal choice is an integration of what one wants and what one believes is possible, suggesting that goals are realistic. In this vein, Kőszegi and Rabin (2006, 2009) assume that when making decisions and plans, reference-dependent individuals endogenously form reference points that must satisfy rational expectations.

The consumer's sign-up decision and subsequent goal choice also depend on her beliefs about future behavior, particularly the degree to which she is aware of her time inconsistency. To capture the full spectrum of beliefs, we use O'Donoghue and Rabin's (2001) model of partial naivete, in which the consumer may be aware of her time-inconsistency but may underestimate its magnitude. The concept of partial naivete generalizes the polar cases of naive and sophistication (O'Donoghue and Rabin 1999), and allows us to explore the effect of belief heterogeneity on observed behavior in the actual program.[14] Let $\hat{\beta}$ be her period-0 belief about parameter β, with which she actually makes the consumption decision in period 1. In period 0, she evaluates utility according to (the true) β, but she *believes* that in the future, she will make decisions based on $\hat{\beta}$, where $\hat{\beta} \in [\beta, 1]$. When $\hat{\beta} = \beta = 1$, the consumer is a standard exponential discounter, and is thus time-consistent. When $\hat{\beta} = \beta < 1$, the consumer is sophisticated, fully aware of her time inconsistency. When $\beta < \hat{\beta} = 1$, the consumer is naive, completely unaware of her time inconsistency and extremely optimistic about her ability to implement ex-ante plans.

When the goal is determined by expectations, the consumer *believes* that she will choose (x^*, y^*) according to $\hat{\beta}$ rather than β. Since her goal matches these expectations, then $r = x^*(\hat{\beta})$.

[14] Ali (2011) derives the conditions under which partial naivete can arise when an individual can learn about the severity of her self-control problem through experimentation.

Let $V(x^*(\hat{\beta}), y^*(\hat{\beta}) | r = x^*(\hat{\beta}))$ be her perceived indirect utility from signing up for the program, given goal $r = x^*(\hat{\beta})$. When $r = x^*(\hat{\beta})$, the consumer expects to receive zero comparison utility from meeting her goal. Let $V(\tilde{x}(\hat{\beta}), \tilde{y}(\hat{\beta}))$ be her perceived indirect utility from not signing up, where $(\tilde{x}, \tilde{y})$ is her consumption if she does not sign up:

$$V(x^*(\hat{\beta}), y^*(\hat{\beta}) | r = x^*(\hat{\beta})) = u(x^*(\hat{\beta}), y^*(\hat{\beta})) + g(x_0 - x^*(\hat{\beta})) - \delta c(x^*(\hat{\beta})) \tag{4.4}$$

$$V(\tilde{x}(\hat{\beta}), \tilde{y}(\hat{\beta})) = u(\tilde{x}(\hat{\beta}), \tilde{y}(\hat{\beta})) - \delta c(\tilde{x}(\hat{\beta})). \tag{4.5}$$

When she is not in the goal-setting program, she has no additional motivation to consume less electricity, so $\tilde{x}(\hat{\beta}) \geq x^*(\hat{\beta})$. Based on her beliefs, the consumer signs up for the program if its discounted net benefits outweigh its sign-up cost.

In the absence of reward points, a consumer who believes she will not overconsume in the future ($\hat{\beta} = 1$) would not sign up for the program even if $\varepsilon = 0$, since she believes that goals would distort optimal behavior. Thus, time-consistent and naive consumers will only sign up if reward points are sufficiently attractive. On the other hand, a consumer with a low (true) β is less inclined to sign up, since she does not value the future benefits from sign-up sufficiently relative to the immediate sign-up cost. Thus, consumers who recognize their need for self-control are more inclined to sign up for the goal-setting program ($\hat{\beta} < 1$). If reward points are not sufficiently attractive for time-consistent and naive consumers to sign up, they are certainly not sufficient to induce sign-up by sophisticated hyperbolic discounters, who anticipate earning fewer rewards due to the tendency to overconsume. In this case, program sign-up is driven by the desire to curb overconsumption due to present-biasedness.

Proposition 2 *When goals are determined by expectations, time-consistent ($\beta = \hat{\beta} = 1$) and naive ($\beta < \hat{\beta} = 1$) consumers only sign up for the goal-setting program if reward points are sufficiently attractive. Otherwise, a consumer must recognize her own time inconsistency to sign up for the program ($\hat{\beta} < 1$).*

When goals are determined by expectations, those who sign up and have more optimistic beliefs about their self-control (i.e., higher $\hat{\beta}$) will set more ambitious consumption goals (i.e., lower r), because they expect to achieve them. But those who are partially naive ($\beta < \hat{\beta}$) will fall short of them, since they are more present-biased than they had believed.

Proposition 3 *When goals are determined by expectations, consumers who have signed up for the goal-setting program will either meet their goals (when fully sophisticated) or fall short of them (when partially naive).*

Freely Chosen Goals. We now consider the implications of an alternative model, where the consumer is an expected utility (EU) maximizer, neither reference-dependent nor present-biased. This is equivalent to assuming that $\hat{\beta} = \beta = 1$ and that $f(r-x) = 0$ for all x. The key difference between the standard EU maximizer and the reference-dependent consumer is that after sign-up, the former is not affected by the self-set goal at all. However, her behavior *is* affected by the presence of reward points, which affect her material outcome. She will be motivated by reward points to consume less electricity if they are negatively correlated with consumption.

Because the self-set goal (r) is completely divorced from the consumer's material payoff, her goal choice is completely irrelevant to her utility. Thus, there should be no correlation between her goal choice, r, and actual consumption. Here, the consumer has no self-control problem to mitigate, so she will sign up only if earning reward points outweighs their distortionary effect of reducing her consumption.

Proposition 4 *When the consumer is not reference-dependent, the selected goal is unrelated to actual consumption. Moreover, she will certainly consume less electricity after signing up for the program if she earns reward points from doing so.*

Thus, the two models of consumer preferences offer very different predictions about program sign-up and subsequent goal selection. When the consumer is reference-dependent and present-biased, she will only sign up if she desires commitment, and she will set realistic or overly-optimistic goals relative to her actual consumption. When the consumer is a standard EU maximizer, she will sign up purely to earn reward points. Because the accumulation of reward points is unrelated to the self-selected goal, her goal choice should be unrelated to actual consumption.

5 Model Evaluation

We evaluate whether the models' predictions are supported by first examining the link between goal choice and savings, then turning to program adoption and goal choice. Table 1 summarizes our empirical findings and the predictions of potential mechanisms. While various forms of the EU model cannot explain the results, we find support for the model of reference-dependent, present-biased preferences.[15]

Goal Choice and Savings. The selection of goals that are either realistic or over-optimistic (i.e., between 0% and 50% savings) is consistent with consumers who are partially naive or sophisticated and who set goals that are consistent with their (over-optimistic or realistic, respectively) expectations. Because the goal is entirely divorced from reward points, it is also possible that consumers are simply EU maximizers, who can set any levels of goals since they are payoff-irrelevant anyway.

Figure 2 shows that consumers choosing realistic goals achieve the most substantial savings of 11% on average, indicating that their goals tend to be in line with actual consumption. By contrast, consumers choosing no goals save about 1.5% on average, while those choosing over-optimistic goals save on average only 1% savings. Consumers with unrealistic goals show no statistically significant change in their consumption behavior in response to goals. Moreover, the yearly average savings achieved by the over-optimistic and unrealistic consumers are driven by their behavior in the first two months. These consumers quickly give up, realizing that they cannot achieve the projected savings. Together, these findings are consistent with the reference-dependent model, which predicts an approximately inverse U-shaped relationship between goal choice and

[15] Additional specifications and robustness checks are available in the Appendix.

savings. Those who set realistic goals achieve correspondingly increasing savings, while those who are partially naive will fall short of self-set goals and actually save less as the savings goal increases, due to diminishing sensitivity to relative losses. Since the goal is not payoff relevant, any relationship, or lack thereof, between goal choice and post-adoption savings would be consistent with the EU model.

As previously discussed, the email feedback and points awarded, which were based on weather-adjusted usage from the previous year, were very noisily related to actual behavior. Consumers received similar rewards irrespective of the actual savings achieved or the goals chosen. Thus, consumers who sign up solely to earn reward points should quickly give up saving once they realize this. While the initial saving and subsequent drop-off in savings among those consumers who set 0% and overly ambitious savings goals is consistent with the EU model, the persistent and substantial savings among those who set realistic goals indicates that pure points-seeking is not a sufficient explanation for adoption and post-adoption behavior.

We now evaluate the prediction that before enrolling in the program, present-biased consumers are likely to consume more electricity than consumers who are not present-biased. In Panel (A) of Table 4 we regress monthly consumption before adoption on the household characteristics. The estimates suggest that variables associated with present-biasedness tend to have a (weak) positive effect on pre-adoption usage, indicating that present-biased consumers may in fact tend to consume more electricity. Statistically however, mean consumption is strongly driven by demographic factors such as household size and income.

Our reference-dependent, present-biased model predicts that present-biased consumers also achieve lower post-adoption savings than those who are not. We restrict our attention to households who have chosen realistic goal, then further divide such households into subgroups as a function of the different characteristics and estimate the "event study" accounting for potential heterogeneity between the different subgroups. In Figure 3 we show the estimated savings (ignoring the period before adoption where consumption is the same) for two of our variables: dieting and loan-to-value ratio in excess of 80%.[16] We find that dieters and those with high loan-to-value ratios save significantly less than non-dieters and those with lower loan-to-value ratios, respectively. For each of these variables, an analysis of households that includes both realistic and overly optimistic goals reveals an even wider gap in savings between subgroups, though average savings by both subgroups is unsurprisingly higher, since overly optimistic households save less on average than realistic ones. In contrast, the EU model, which precludes self-control problems by assumption, predicts no systematic relationship between indicators of demand for self-control and pre- and post-adoption consumption.

Program adoption. A household is considered an adopter if she successfully "linked" her utility account to the CUB website. We assume that the households we observe from the voter registration lists had the opportunity to opt-in but did not. Thus, a natural way to investigate the characteristics of the adopters is to conduct a logit analysis on the decision to opt-in as function of the observable demographics, corresponding to a simple linear random utility choice model.[17] The estimated coefficients are displayed in Panel (B) of Table 4. Column 2 shows that smaller, more educated households who are concerned for the environment are more likely to opt in. We find that smoking is a significant negative predictor of adoption, while dieting is a significant driver of adoption, suggesting that recognition of present bias is relevant for sign-up. Dieters are more likely to be aware of time inconsistency and the need for commitment, since they seek additional intervention to curb caloric intake. Smoking in itself does not reliably predict the need for commitment, since smokers can include smokers who don't want to quit. A high loan-to-value ratio is a positive and significant predictor of adoption, while having one or more store credit lines is a negative predictor. Both groups are likely to be present-biased, but given the recent collapse in the housing market and its severity, it is probable that the former is very much aware of its time inconsistency.

[16] We estimate similar specifications for all demographic variables. We find that on average, the group of consumers that is tagged as more likely to be present-biased saves less after adoption for variables for which we have sufficient observations to estimate the model by characteristic.

[17] In the Appendix, we explain why the logit model consistently estimates the slope parameters in the context of a retrospective sample.

Columns 3-6 of Table 4 report the estimated coefficients of multinomial logit regressions, where the categories correspond to the fractions of committed savings to past usage (0%, 0%-15%, 15%-50%, 50%+) and the baseline category consists of consumers in the control group who have not signed up for the program. Education is a major driver of setting realistic goals. “Green” consumers and dieters appear to be more likely to choose overoptimistic goals in the range 15%-50%. In Column 7 of Table 4 we estimate a Negative Binomial model on the number of chosen actions that the consumers commit to. Education, especially a graduate degree, act as a moderating force on the number of actions committed to by a consumer. Green living predicts a higher number of committed actions, which may indicate that some consumers may select actions they have already done. In Columns 8-10, we estimate OLS regressions on the absolute level of goal-implied savings in terms of kWh. Wealthier households choose higher absolute levels of savings, reflecting their greater savings opportunities. Education continues to act as a moderating influence. Thus, dieting indicates a propensity to set overly optimistic goals, both in the number actions and in their implied savings. That they tend to be over-optimistic may be not surprising, in light of the fact that dieting itself is often an unsuccessful exercise. Since dieters are a group who exhibit a demand for commitment, their behavior is consistent with the behavioral model’s prediction that those who recognize their self-control problem and their reference-dependence will set goals to counteract overconsumption. The EU model again predicts no systematic relationship between indicators of demand for self-control and adoption or goal choice.

In sum, realistic goals lead to persistently higher post-adoption savings than other goal levels despite ineffectual material incentives in the form of reward points. Indicators of demand for commitment predict higher pre-adoption and post-adoption consumption, as well as overly-optimistic goal choices, relative to their absence. Taken together, this evidence is consistent with the predictions of the behavioral model but cannot be easily reconciled with the expected utility model.

Alternative Mechanisms. Because the CUB program website includes reward points, personal goal-setting and energy-saving tips, the exact mechanism through with post-adoption savings occurs cannot be conclusively identified here. However, the observed pattern of post-adoption behavior is highly suggestive that information and reward points are not the sole drivers.

While we argue that behavior is driven by reference-dependent preferences, an alternative explanation is that non-binding personal goals are irrelevant to consumers, and that they are expected utility (EU) maximizers who sign up because they may want to reduce their electricity bills but have uncertainty about how to save effectively, which the energy-saving tips clarify. Thus, they have no self-control problem and their goal choice is irrelevant for behavior. However, the evidence from the CUB program indicates that at least some proportion of consumers do not satisfy these predictions. First, consumers who exhibit demand for commitment in other domains (i.e., dieters or risky borrowers) are more likely to sign up than those who do not. Second, the relationship between self-set goals and savings behavior is not random. Moreover, at the action selection stage, all consumers are exposed to the full array of energy-saving tips, of varying investment cost and efficiency impact, *before* they select non-binding goals. Thus, it is not the case that consumers with higher goal levels are exposed to more difficult actions than those with lower goal levels. Consumers who select over-optimistic goals tend to select more actions that entail larger investments, which is unsurprising since these would generate the largest savings if actually implemented. However, there is no significant difference in the selection of low-cost behavioral actions across consumers with different goal levels. The degree of goal ambition is driven by the number of actions, rather than the type selected.

Another explanation is that consumers are EU maximizers who are information-seeking and interested in reward points, but their self-selected goals are reflective of underlying preferences, rather than random choices. But to explain the observed relationship between goals and consumption, it would have to be the case that those who set 0-15% savings goals actually wanted to save this amount (or earn the corresponding number of points), yet those who set above 15% savings goals actually wanted to save *less* than the 0-15% group (or earn fewer points). We find this quite unconvincing. If goals reflect underlying preferences, it is much more plausible that those who set less ambitious goals wish to save less, or are less motivated by points, than those who set more ambitious goals, who wish to save more or are more motivated by points. However, the non-monotonic relationship between goal level and savings behavior—in particular, that those who set goals above 15% actually save less than those who set goals under 15%, and yet those who set exactly 0% goals *also* save less than those who set positive but realistic goals—belies this, and is instead predicted by the model of reference-dependent preferences.

To further distinguish whether consumers are driven to save due to non-binding goal-setting or energy-saving tips, we conducted a field experiment in which goals were assigned by the firm, rather than self-set, and reward points did not exist. The experiment was conducted by direct mail in Western Massachusetts during 2011. Approximately 5000 households were randomly assigned to a treatment where they received information on how to save electricity every quarter. Another 5000 households were assigned to a treatment where they were given an energy saving goal; then every quarter, they received additional feedback on whether or not they were meeting their goal and on the amount they saved or did not save during the period between mailers. Thus, in the goals-centered treatment, there is no material benefit from savings awarded by the firm, and goals are assigned, unlike in the CUB program. A randomly chosen control group of approximately 25,000 households did not receive any form of treatment. The precise details and investigation of this field experiment are discussed in Harding and Hsiaw (2012). For the purpose of our discussion, we only provide reduced-form evidence from this field experiment.

Although the groups were randomized, a certain degree of imbalance was introduced in the experiment when the utility selected certain consumers based on previous usage which was deemed to high or too low or in some other way unreliable and removed from the treatment group. This introduced a small but noticeable amount of selection bias. Therefore, in Table 5, we report difference-in-differences estimates of the treatment effect of for the period after the start of the experiment compared to the same period one year prior. To verify the robustness of the results to potential selection bias, we also report difference-in-differences estimates with matching, where we used either moments of the consumption distribution or the sequence of monthly usage amounts during 2010 as matching variables (Heckman, Ichimura and Todd 1998).

Compared to a baseline treatment in which consumers were only given energy-saving tips, consumers who were given both energy-saving tips and personal, non-binding goals saved between 1.3% and 2.1%. The consumers who were provided with energy-saving tips alone did not save any electricity relative to the control group, which received neither energy-saving tips nor goals. This suggests that neither information-seeking nor reward point maximization is sufficient to explain post-adoption savings.

The CUB program also provided consumers with information on the "ranking" of their community in terms of savings relative to other communities. As we mentioned before, we do not believe that this aspect of the program had a confounding effect. Evidence from the activity on the website shows that this feature of the program was the least utilized and rarely looked at. The field experiment we conducted provides additional evidence that consumers do not react to such ranking information. The experiment introduced one additional treatment where consumers were told about their rank relative to their peers, in addition to being given energy savings tips. This piece of information could potentially have motivated consumers to a greater degree than by providing them with information about the rank of their community. The statement itself is very ambiguous, as it is not clear what the consumer will conclude about everyone else's actions and how they will affect her rank, even if she decided to act on this information. Thus, as expected, we did not find any evidence that this treatment changed energy consumption behavior compared to the control group, who did not receive any rank information.

In the Appendix, we extend our model to allow for implementation costs. The theoretical insights remain qualitatively very similar. Empirically, it is very challenging to consider ways of quantifying the costs to the consumer of implementing a specific savings plan, since many of the chosen actions are financially costless but may entail unobservable inconvenience or time costs. A team of C3 engineers created an estimated score of the cost to the user of implementing each action to supplement the observed financial cost. While this measure is clearly very noisy, it may still be informative. A careful analysis of this data does not support implementation costs as an explanation of the observed savings patterns in the data. In particular, it does not support the idea that households choosing more difficult actions are less likely to save or to save persistently.

Our analysis addresses a leading explanation in the existing environmental literature on energy conservation (e.g. Kotchen and Moore (2007)), that individuals are driven by altruistic concerns for the environment or social well-being, which is adversely affected by environmental factors. While this is entirely consistent with a desire to consume less electricity (as we acknowledged in describing and interpreting the model), altruism is neither necessary nor sufficient to explain why consumers would opt into the goal-setting program in the first place. If they were altruistic and time-consistent, they would have no difficulty implementing plans to consume less electricity. Thus, the only appeal of the program to such time-consistent altruists would be its informational value or reward points, if they are uncertain about how to save electricity and view the program as a source of information or if they want to earn points. However, we have already demonstrated that neither of these motivations are sufficient to explain the results.

Taken together, the evidence from the CUB program and the field experiment strongly corroborates with the theory that a measurable, non-trivial proportion of consumers 1) have a tendency to overconsume electricity relative to their ex-ante preference, and 2) possess reference-dependent preferences, where the goal acts as a reference point and is determined by expectations. These findings are quite difficult to reconcile with standard EU preferences, particularly seeking reward points and seeking information. In our view, the most parsimonious explanation is that individuals seek the goal-setting program because they are aware that they have a tendency to overconsume due to present-biasedness. Because they are reference-dependent, they are aware that they will respond to even non-binding goals, and attenuate their consumption.

6 Conclusion

This paper shows that goal setting can be an effective behavioral nudge for reducing residential energy consumption. It evaluates the implementation of a program in Northern Illinois, where consumers are asked to choose an energy savings goal, and then provided with information and feedback designed to help them implement a series of energy efficiency and conservation actions.

We provide a theoretical model in which consumers have present-biased preferences, which lead them to overconsume, and reference dependent preferences, where goals influence behavior by serving as reference points. We identify this behavioral mechanism in the data and show that consumers achieve substantial savings. While on average consumers save 4%, savings are very heterogeneous. Consumers who set realistic goals persistently achieve substantially higher savings than those who do not. We consider and rule out several alternative explanations for the adoption decision and post-adoption behavior, including points-seeking and information-seeking. Thus, the evidence suggests that interest in energy-saving programs is driven by consumers' recognition of their present bias, and that goal setting can be quite effective at reducing energy consumption when goals are achievable.

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Figure 1: Estimated percent savings from program adoption in event time. Month 0 denotes the month before sign up.

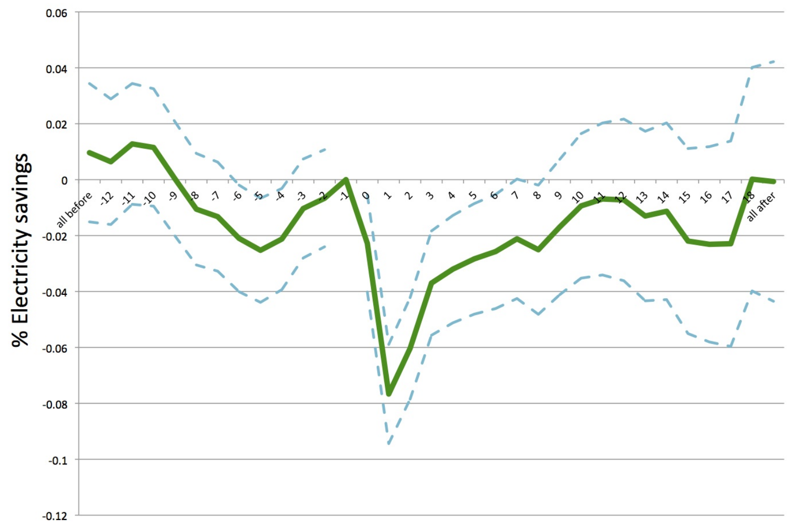

Figure 2: Heterogeneity in electricity savings after program adoption in relation to the chosen goal.

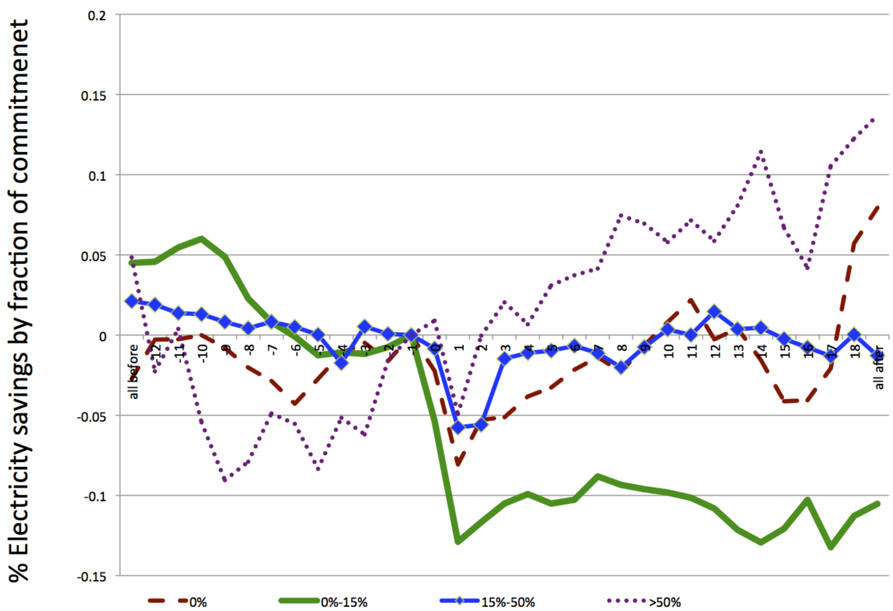

Figure 3: Heterogeneity in electricity savings after program adoption for consumers who choose realistic goals as a function of individual characteristics.

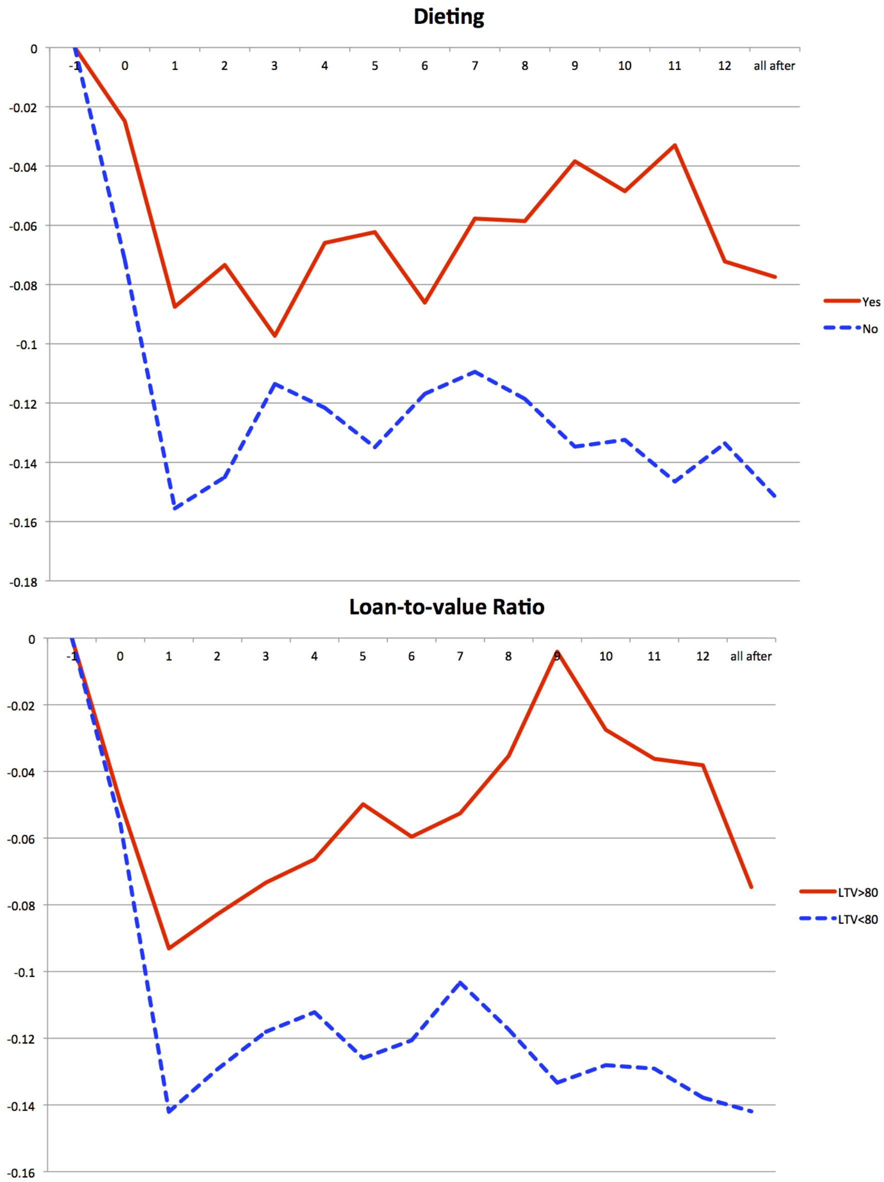

Table 1: Empirical findings and model predictions.

		Model Prediction			
Feature	**Finding**	**Expected Utility (EU)**	**EU, info-seeking**	**EU, info-seeking, goals reflect preferences**	**Reference-dependent, hyperbolic**
Post-adoption savings	Positive (except infeasible goals)	Positive/Zero* (for any goals)	Positive (for any goals)	Positive (for any goals)	Positive (for positive goals)
	Hyperbolics save less	No difference	No difference	No difference	Hyperbolics save less
Goal level vs. savings	Positive when realistic; Negative when not realistic	None/any	None/any	Positive	Positive when realistic; Negative when not realistic
Adoption	Sophisticated hyperbolics more likely	No difference	No difference	No difference	Sophisticated hyperbolics more likely
Pre-adoption consumption	Hyperbolics consume more	No difference	No difference	No difference	Hyperbolics consume more
Field Experiment**	More savings with goals	Same savings with goals	Same savings with goals	Same savings with goals	More savings with goals

Since EU models assume no self-control problems, they predict no differences in behavior by variables consistent with hyperbolics.

* If reward points are negatively correlated with electricity consumption, EU consumers will save after signing up for the program. But if reward points are uncorrelated with electricity consumption, EU consumers' behavior will not change upon adoption.

** No consumers in the field experiment earned reward points. In one treatment, they received information on energy-saving tips only. In another, they received information on energy-saving tips as well as assigned, exogenous goals. We compare the models' predictions about savings in the latter treatment relative to the former.

Table 2: Summary statistics for CUB Adopters and a random control group of Northern Illinois households.

	Mean		Standard Deviation		
	Control	Adopters	Control	Adopters	p-val
Demographic Variables					
Age 35-65	0.761	0.762	0.426	0.426	0.930
Age 65+	0.403	0.277	0.490	0.448	0.000
HH income 75k-125k	0.289	0.318	0.453	0.466	0.005
HH Income 125k +	0.178	0.190	0.383	0.392	0.190
College	0.316	0.353	0.465	0.478	0.000
Graduate School	0.179	0.251	0.383	0.433	0.000
Children	0.373	0.355	0.484	0.479	0.090
Household Size	3.226	2.954	1.591	1.507	0.000
Environmental Variables					
Environmental Issues	0.176	0.224	0.381	0.417	0.000
Green Living	0.369	0.408	0.483	0.492	0.000
Self-Control Variables					
Smoker	0.057	0.051	0.231	0.221	0.309
Dieting	0.353	0.403	0.478	0.491	0.000
Gambling-Lottery	0.059	0.066	0.236	0.248	0.221
Gambling-Casino	0.137	0.141	0.344	0.348	0.675
Financial Variables					
Home loan to value 80% or +	0.215	0.265	0.411	0.441	0.000
Credit Line	0.751	0.703	0.432	0.457	0.000

Table 3: Estimation of the post-adoption savings using propensity score matching.

	(I)	(II)	(III)	(IV)	(V)
ATT	-0.044	-0.029	-0.044	-0.031	-0.031
	(.009)	(.033)	(.037)	(.023)	(.027)
Matching variables					
Demographics		Y	Y	Y	Y
2009 usage		Y	-	Y	-
Matching method		Y	Y	-	-
Nearest Neighbor		-	-	Y	Y
Nearest 5 Neighbors					

Standard errors Models (II)-(V) were obtained using the bootstrap.

Table 4: Evaluating the model predictions in relation to usage and savings.

	(A)	(B)						(C)		
log(kwh)	Usage	Linking	Adoption by level of goal				Number	log(kwh savings) by goal		
	Before		0%	0%-15%	15%-50%	>50%	of actions	0%-15%	15%-50%	>50%
Age 35-65	0.0472	-0.258*	-0.567*	-0.159	-0.221	-0.499	0.0953	0.0601	0.00389	0.169*
	(0.0309)	(0.131)	(0.226)	(0.173)	(0.129)	(0.265)	(0.0542)	(0.0670)	(0.0429)	(0.0811)
Age 65+	-0.0736*	-0.700***	-0.661***	-0.748***	-0.734***	-0.702**	0.0190	-0.0224	-0.0321	0.129
	(0.0291)	(0.0970)	(0.194)	(0.142)	(0.123)	(0.256)	(0.0537)	(0.0634)	(0.0419)	(0.0873)
HH income 75k-125k	0.170***	0.0871	0.157	0.0307	0.117	0.0386	0.100*	0.113*	0.193***	0.187*
	(0.0251)	(0.0557)	(0.119)	(0.101)	(0.0745)	(0.161)	(0.0478)	(0.0569)	(0.0367)	(0.0815)
HH Income 125k +	0.248***	0.0187	0.247	0.0313	-0.0488	-0.158	-0.0254	0.139*	0.241***	0.208
	(0.0318)	(0.0936)	(0.129)	(0.140)	(0.108)	(0.201)	(0.0582)	(0.0665)	(0.0459)	(0.109)
College	0.0126	0.323***	0.385*	0.391***	0.292***	0.193	-0.115*	0.0310	-0.00513	-0.148
	(0.0265)	(0.0598)	(0.153)	(0.0860)	(0.0764)	(0.147)	(0.0483)	(0.0582)	(0.0371)	(0.0803)
Graduate School	-0.000237	0.550***	0.518**	0.717***	0.458***	0.449*	-0.217***	-0.0827	-0.0852*	-0.135
	(0.0293)	(0.107)	(0.161)	(0.142)	(0.115)	(0.218)	(0.0546)	(0.0648)	(0.0429)	(0.0926)
Children	-0.00780	-0.0187	-0.141	-0.0220	-0.0123	0.268	0.0515	0.0595	-0.0154	0.0569
	(0.0284)	(0.0691)	(0.138)	(0.112)	(0.0879)	(0.167)	(0.0545)	(0.0613)	(0.0414)	(0.101)
Household Size	0.106***	-0.106***	-0.103*	-0.0419	-0.101**	-0.425***	-0.0119	0.0255	0.0690***	0.0195
	(0.00945)	(0.0240)	(0.0488)	(0.0357)	(0.0322)	(0.0677)	(0.0183)	(0.0205)	(0.0139)	(0.0397)
Environmental Issues	-0.0473	0.222**	0.117	0.137	0.294**	0.238	0.100	-0.101	-0.00645	0.102
	(0.0328)	(0.0692)	(0.160)	(0.116)	(0.0961)	(0.197)	(0.0643)	(0.0781)	(0.0482)	(0.119)
Green Living	0.0555	0.0992	-0.0103	0.0581	0.169*	0.136	0.156**	0.226**	0.0502	0.134
	(0.0310)	(0.0608)	(0.136)	(0.125)	(0.0844)	(0.144)	(0.0599)	(0.0686)	(0.0461)	(0.108)
Smoker	0.0684	-0.265*	-0.0223	-0.235	-0.349*	-0.362	0.0214	0.117	0.0269	0.00774
	(0.0487)	(0.114)	(0.246)	(0.173)	(0.155)	(0.391)	(0.0958)	(0.117)	(0.0737)	(0.176)
Dieting	0.0360	0.273***	0.215	0.146	0.382***	0.297*	0.130*	-0.0249	0.129***	0.154
	(0.0257)	(0.0715)	(0.150)	(0.102)	(0.0871)	(0.140)	(0.0510)	(0.0602)	(0.0385)	(0.0887)
Gambling-Lottery	0.00608	0.106	-0.0536	0.174	0.114	0.0307	-0.00478	0.0284	-0.0271	0.127
	(0.0459)	(0.110)	(0.246)	(0.173)	(0.146)	(0.299)	(0.0946)	(0.114)	(0.0703)	(0.183)
Gambling-Casino	0.0801*	-0.0406	-0.165	-0.0906	0.0206	-0.0907	0.0163	-0.0511	0.111*	-0.107
	(0.0353)	(0.0802)	(0.197)	(0.135)	(0.101)	(0.192)	(0.0699)	(0.0840)	(0.0529)	(0.125)
Home loan to value 80% or +	0.0780***	0.234***	0.371**	0.181	0.280**	0.00275	-0.0106	-0.0172	0.0576	0.0391
	(0.0235)	(0.0710)	(0.116)	(0.0999)	(0.0877)	(0.187)	(0.0472)	(0.0547)	(0.0363)	(0.0886)
Credit Line	0.0413	-0.241**	-0.301	-0.0916	-0.283**	-0.311**	0.0527	0.163**	0.00162	0.147
	(0.0283)	(0.0821)	(0.187)	(0.111)	(0.0897)	(0.119)	(0.0498)	(0.0603)	(0.0382)	(0.0801)
Constant	5.707***	-0.931***	-2.561***	-2.401***	-1.895***	-2.025***	1.626***	6.237***	7.177***	7.436***
	(0.0684)	(0.111)	(0.246)	(0.188)	(0.142)	(0.218)	(0.0607)	(0.0742)	(0.0475)	(0.0943)
Observations	28090	12,498	10,374	10,791	11,035	10,272	2487	790	1034	271
R-squared	0.187	0.035	0.028	0.027	0.036	0.053		0.066	0.135	0.203

Standard errors in parentheses, * p<0.05 ** p<0.01 *** p<0.001; constant not reported

Table 5: Difference-in-differences estimation of different treatment conditions in a field experiment setting.

	(I)	(II)	(III)
Information	4.236	-0.745	5.55
	(2.636)	(18.213)	(20.234)
Goals	-9.167	-14.719	-12.265
	(2.221)***	(23.003)	(15.180)
Rank Comparison	0.675	-3.896	-1.858
	(2.362)	(52.320)	(37.930)
Matching Variables			
2010 Moments	-	Y	-
2010 Bills	-	-	Y

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

Average monthly usage in 2011: 690 kWh

For Online Publication

Additional Details on the CUB Program

The program provides monthly emails as soon as a new bill is received. The feedback provided through emails is limited, as customers cannot receive negative feedback (i.e., the customer is told that she used the same or more energy than in the same month last year, but not exactly how much more). The "savings" feedback received through monthly emails is adjusted for weather and seasonality according to a proprietary algorithm that is not disclosed to customers (nor to us).[18] However, this computation makes no comparison to the self-selected goals. We later show that weather-adjusted feedback is quite noisy and is poorly correlated with actual consumption in the data. The extent to which feedback emails are actually opened by consumers is technically challenging to measure, as many ISPs do not provide this information. However, a lower bound from reporting ISPs indicates that at least 53% of emails are opened each month. This indicates that consumers remain engaged with the program. The website can also display weather-adjusted savings relative to the same month last year, just as in the monthly email feedback.

Consumers are also awarded "points," which can be redeemed for coupons for local retailers from a third party website. Points are awarded on a monthly basis, if the consumer reduces monthly consumption relative to her weather-adjusted usage the year before, according to a procedure which is not available to the consumer. Just as with the monthly email feedback, points are *not* awarded based on consumption relative to the self-selected goal. The consumer does not lose points if she does not save relative to past usage, and the maximum number of points awarded is capped. Thus, points are only very noisily correlated to actual savings, and do *not* act as a material incentive for consumers to achieve their selected goals. We do not have access to information on point redemption, but anecdotal evidence suggests point redemption is extremely low. Moreover, a customer survey indicates that fewer than 15% of consumers report rewards as the reason for

[18] We know, however, that the website does not adjust consumption for common factors, e.g. after accounting for weather factors, if everyone uses less electricity this year as a result of the economic recession than last year, this is not taken into account.

signing up for the program.

Given that the program reports weather-corrected savings in various forms that are each quite noisy and are not explicitly linked to the self-selected goal, we believe that the most useful and straightforward information for customers to extract from the program is the unaltered monthly billing information in the current year and in the same month last year, which includes monthly usage in kWh and in dollars and is not weather-adjusted. From this, they can easily compute and monitor their monthly consumption relative to the monthly goal estimate, regardless of the website algorithm's noisy weather-adjusted computations. In the analysis that follows, we compute savings in this manner as well, while statistically accounting for common factors.

It is important to note that in this program, consumers do not receive social comparisons feedback, where consumers are compared to similar neighbors, as discussed by Allcott (2011). Consumers have some very limited ability to compare their savings to other participants in the same "community," where communities are very broadly defined at the town level. Consumers also receive information stating the "rank" of their community relative to other communities in terms of achieved savings. The page reporting these comparisons appears to be the least visited page on the website. Since the overall number of adopters is relatively low, this information is very noisy, and as we shall show later, consumers do not know how to use this information. Therefore we will abstract from these potential confounds, as we believe that they provide noisy and unreliable information which the consumers do not utilize.

Robustness of Savings Behavior Using Matching

Our estimate of the extent to which households save as a result of this program may depend on the extent to which individuals with different characteristics opt into the program at different points in time. To evaluate the robustness of these savings estimates, we use propensity score matching to account for the potentially varying demographics of the adopters over time as they select into the program. We follow the method for computing the average treatment effect on the treated (ATT) introduced in Sianesi (2004), by comparing those individuals who adopt at time t with those who have not adopted up until t (they adopt in future periods), while correcting for discrepancies in observables.

First, we determine the treatment and control groups. Each period u has its own treatment and control group. The treatment is starting the program in month u. The control group at time u is composed of all those that have not joined the program yet. Formally, let D_{it} be equal to 1 if the individual i had join the program by period t. Then the treatment and the control groups at time u, T^u and C^u respectively, are defined as follows:

$$i \in T^u \Leftrightarrow D_{iu} = 1 \ \& \ D_{it} = 0 \ \forall t < u$$

$$i \in C^u \Leftrightarrow D_{it} = 0 \ \forall t \leq u.$$

In our case, we consider 19 months (June 2010-December 2011) when the individuals could have adopted, i.e. $u = 1, 2, \ldots, 19$. Hence, we have 19 control and treatment groups.

Second, for each period u we are interested in obtaining the average impact at time t in log electricity usage, for those adopting the program in their u^{th} month, $\triangle_t^u$. $\triangle_t^u$ is defined as:

$$\triangle_t^u \equiv E(Y_t^{1(u)} - Y_t^{0(u)} | D^{(u)} = 1); \ t \geq u. \tag{6.6}$$

Each $\triangle_t^u$ is estimated using propensity score matching. For each of the 19 treatment and control groups, we perform propensity score matching to obtain the ATT on log usage at time t. We match on the available demographics and on pre-adoption monthly usage, and also employ several varieties of the nearest neighbor method for matching.

Finally, we are interested in the synthetic overview of adoption's effect at time t. That is, we want to know the effect on electricity usage at period t after adoption, independently of when the individual adopted. Hence, we compute the average $\triangle_t^u$, by weighting the different ATT's by the proportion of treated that join in period u:

$$E_U(\triangle_t^u | D = 1) = \sum_{u \leq t} E(Y_t^{1(u)} - Y_t^{0(u)} | D(u) = 1) \times P(D^{(u)} = 1 | D = 1), \tag{6.7}$$

where $P(D^{(u)} = 1|D = 1)$ is estimated as the number of individuals that joined in period u over the total individuals that joined up to period t. We compute the standard errors by 500 bootstrap repetitions.

For presentational simplicity, we summarize the estimation results in Table 3 by reporting the average of the estimated savings over the post-adoption period (instead of reporting period by period estimates). Model (I) estimates the difference-in-differences equation (Equation 3.1) using one post-adoption indicator. The average estimated post-adoption savings for consumers who opt in is 4.4%. The different matching approaches produce estimates ranging from 2.9% to 4.4%.[19]

Proof of Proposition 1

In the second stage, the goal r is taken as given by the consumer. Assuming an interior solution, the consumer's optimal consumption given a goal, (x^*, y^*), satisfies the first order condition when the consumer has signed up, where $px^* + y^* = m$:

$$\frac{\partial u}{\partial x}(x^*) - p(\frac{\partial u}{\partial y}(y^*)) - [f'(r - x^*) + g'(x_0 - x^*)] - \beta\delta c'(x^*) = 0. \tag{6.8}$$

If the consumer does not sign up for the program, then her optimal consumption $(\tilde{x}, \tilde{y})$ satisfies the following condition, where $p\tilde{x} + \tilde{y} = m$:

$$\frac{\partial u}{\partial x}(\tilde{x}) - p(\frac{\partial u}{\partial y}(\tilde{y})) - \beta\delta c'(\tilde{x}) = 0. \tag{6.9}$$

[19]Note that the standard errors increase as a result of the matching algorithm utilizing only a small subset of the observations at each step. This is unavoidable given the limited data available.

Applying the implicit function theorem to Equations 6.8 and 6.9 yields:

$$\frac{\partial x}{\partial \beta} = \frac{\delta c'(x)}{\frac{\partial^2 u}{\partial x^2} + 1_{signup}[f''(r-x) + g''(r-x)] + p^2(\frac{\partial^2 u}{\partial y^2}) - \beta\delta c''(x)} < 0 \tag{6.10}$$

$$\frac{\partial x}{\partial r} = \frac{f''(r-x)}{\frac{\partial^2 u}{\partial x^2} + f''(r-x) + g''(r-x) + p^2(\frac{\partial^2 u}{\partial y^2}) - \beta\delta c''(x)} \tag{6.11}$$

$$\frac{\partial x}{\partial \delta} = \begin{cases} \frac{\beta c'(x)}{\frac{\partial^2 u}{\partial x^2} + 1_{signup}[f''(r-x)+g''(r-x)] + p^2(\frac{\partial^2 u}{\partial y^2}) - \beta\delta c''(x)} < 0 & \text{if } \beta > 0 \\ 0 & \text{if } \beta = 0. \end{cases} \tag{6.12}$$

Note that $\frac{\partial x}{\partial r}$ is positive when $r > x$ and negative when $r < x$, due to diminishing sensitivity to gains and losses.

Proof of Proposition 2

If the consumer is time-consistent or naive ($\hat{\beta} = 1$), she only signs up if

$$\beta\delta[V(x^*(\hat{\beta}), y^*(\hat{\beta}) | r = x^*(\hat{\beta})) - V(\tilde{x}(\hat{\beta}), \tilde{y}(\hat{\beta}))] - \varepsilon \geq 0.$$

When $\hat{\beta} = 1$, then $\tilde{x}(1)$ maximizes $u(x,y) - \delta c(x)$ so

$$u(x^*(1), y^*(1)) - \delta c(x^*(1)) < u(\tilde{x}(1), \tilde{y}(1)) - \delta c(\tilde{x}(1)).$$

Thus, she will only sign up if

$$g(x_0 - x^*(1)) \geq [u(\tilde{x}(1), \tilde{y}(1)) - \delta c(\tilde{x}(1))] - [u(x^*(1), y^*(1)) - \delta c(x^*(1))] + \varepsilon, \tag{6.13}$$

where the right-hand side is strictly positive. If Equation (6.13) is not satisfied, then a consumer with $\hat{\beta} = 1$ does not sign up for the program.

Suppose that Equation (6.13) is not satisfied, and that the consumer is aware of a self-control problem ($\beta < 1$). Since $\frac{\partial x^*}{\partial \hat{\beta}} < 1$, then $g(x_0 - x^*(1)) > g(x_0 - x^*(\hat{\beta}))$, so rewards are less attractive when $\hat{\beta} < 1$ (because the consumer anticipates earning fewer rewards due to her tendency to over-consume). Thus, the consumer's motivation for sign-up is driven by the need for self-control when $\hat{\beta} < 1$.

Implementation Costs

Suppose that the consumer also incurs a cost of implementing goals that result in reductions in energy usage relative to not signing up. Many of the suggested actions for saving energy, such as installing CFLs into lighting fixtures or regularly unplugging appliances after use, require additional effort or inconvenience to implement them. Due to diminishing marginal returns, the cost of saving energy is increasing and convex. The function $h(\tilde{x} - x)$ describes the cost of implementing energy-saving measures, where $\tilde{x}$ is the consumer's energy consumption in the absence of program sign-up:

$$h(0) = 0, \tag{6.14}$$

$$h(\tilde{x} - x) \begin{cases} > 0 & \text{if } \tilde{x} \geq x \\ = 0 & \text{if } \tilde{x} < x, \end{cases} \tag{6.15}$$

$$h'(\tilde{x} - x) \begin{cases} > 0 & \text{if } \tilde{x} > x \\ = 0 & \text{if } \tilde{x} < x, \end{cases} \tag{6.16}$$

$$h''(\tilde{x} - x) \begin{cases} > 0 & \text{if } \tilde{x} > x \\ = 0 & \text{if } \tilde{x} < x. \end{cases} \tag{6.17}$$

We do not model $h(\cdot)$ as a direct function of the goal r, since the consumer would not incur any additional implementation cost if she were to set an unambitious goal that she would exceed without any additional effort (e.g., if $r > \tilde{x} > x$). Rather, implementation costs only are incurred when the agent decides to use less electricity than she would have had she not signed up for the program. The goal indirectly affects implementation costs through its effect on the consumer's consumption decision.

Thus, the consumer's problem in the second stage is

$$\max_{x,y} u(x,y) + 1_{signup}[f(r-x) + g(x_0 - x) - h(\tilde{x} - x)] - \beta\delta c(x) \quad \text{subject to } m \geq px + y, \quad (6.18)$$

where $1_{signup} = 1$ if the consumer signs up for the program and is zero otherwise. When deciding whether to sign up for the program, she takes into account her consumption behavior in response to the goal, her anticipated costs of implementing them, and the reward points she would earn.

With the inclusion of the goal implementation cost, the consumer's energy consumption in the absence of program sign-up, $(\tilde{x}, \tilde{y})$, is still described by Equation (6.9). Her optimal consumption upon sign-up now satisfies Equations (6.19) and (6.20):

$$\frac{\partial u}{\partial x}(x^*) - p(\frac{\partial u}{\partial y}(y^*)) - [f'(r - x^*) + g'(x_0 - x^*) - h'(\tilde{x} - x^*)] - \beta\delta c'(x^*) = 0, \quad (6.19)$$

$$px^* + y^* = m. \quad (6.20)$$

The consumer would never sign up for the program if the cost of goal implementation were so high that she would end up using more electricity after sign-up. Thus, $f'(r - x^*) + g'(x_0 - x^*) - h'(\tilde{x} - x^*) \geq 0$ and $x^* \leq \tilde{x}$. We now re-derive the main propositions for the model with implementation costs.

Proof that $x^* \leq \tilde{x}$ Suppose that $x^* > \tilde{x}$, or equivalently that $\tilde{x} - x^* < 0$. Comparing Equations (6.9) and (6.8), $x^* > \tilde{x}$ only if $f'(r - x^*) + g'(x_0 - x^*) - h'(\tilde{x} - x^*) < 0$. But if $\tilde{x} - x^* < 0$, then $h'(\tilde{x} - x^*) = 0$. Since $f'(r - x^*) > 0$ and $g'(x_0 - x^*) \geq 0$, then it must be that $x^* \leq \tilde{x}$ from Equations (6.9) and (6.8). Thus, $x^* \leq \tilde{x}$.

Proof of Proposition 1*:* Applying the implicit function theorem to Equations 6.8 and 6.9 yields:

$$\frac{\partial \tilde{x}}{\partial \beta} = \frac{\delta c'(\tilde{x})}{\frac{\partial^2 u}{\partial x^2}(\tilde{x},\tilde{y}) + p^2(\frac{\partial^2 u}{\partial y^2}(\tilde{x},\tilde{y})) - \beta\delta c''(\tilde{x})} < 0 \tag{6.21}$$

$$\frac{\partial x^*}{\partial \beta} = \frac{\delta c'(x^*) - h'(\tilde{x}-x^*)(\frac{\partial \tilde{x}}{\partial \beta})}{\frac{\partial^2 u}{\partial x^2}(x^*,y^*) + f''(r-x^*) + g''(r-x^*) - h''(\tilde{x}-x^*) + p^2(\frac{\partial^2 u}{\partial y^2}(x^*,y^*)) - \beta\delta c''(x^*)} < 0 \tag{6.22}$$

$$\frac{\partial x^*}{\partial r} = \frac{f''(r-x^*)}{\frac{\partial^2 u}{\partial x^2}(x^*,y^*) + f''(r-x^*) + g''(r-x^*) - h''(\tilde{x}-x^*) + p^2(\frac{\partial^2 u}{\partial y^2}(x^*,y^*)) - \beta\delta c''(x^*)} \tag{6.23}$$

$$\frac{\partial \tilde{x}}{\partial \delta} = \begin{cases} \frac{\beta c'(\tilde{x})}{\frac{\partial^2 u}{\partial x^2}(\tilde{x},\tilde{y})+p^2(\frac{\partial^2 u}{\partial y^2}(\tilde{x},\tilde{y}))-\beta\delta c''(\tilde{x})} < 0 & \text{if } \beta > 0 \\ 0 & \text{if } \beta = 0. \end{cases} \tag{6.24}$$

$$\frac{\partial x^*}{\partial \delta} = \begin{cases} \frac{\beta c'(x^*)-h'(\tilde{x}-x^*)(\frac{\partial \tilde{x}}{\partial \delta})}{\frac{\partial^2 u}{\partial x^2}(x^*,y^*)+f''(r-x^*)+g''(r-x^*)-h''(\tilde{x}-x^*)]+p^2(\frac{\partial^2 u}{\partial y^2}(x^*,y^*))-\beta\delta c''(x^*)} < 0 & \text{if } \beta > 0 \\ 0 & \text{if } \beta = 0. \end{cases} \tag{6.25}$$

Note that $\frac{\partial x}{\partial r}$ is positive when $r > x$ and negative when $r < x$, due to diminishing sensitivity to gains and losses.

Proof of Proposition 2: If the consumer is time-consistent or naive ($\hat{\beta} = 1$), she only signs up if

$$\beta\delta[V(x^*(\hat{\beta}),y^*(\hat{\beta})|r = x^*(\hat{\beta})) - V(\tilde{x}(\hat{\beta}),\tilde{y}(\hat{\beta}))] - \varepsilon \geq 0.$$

When $\hat{\beta} = 1$, then $\tilde{x}(1)$ maximizes $u(x,y) - \delta c(x)$ so

$$u(x^*(1),y^*(1)) - \delta c(x^*(1)) < u(\tilde{x}(1),\tilde{y}(1)) - \delta c(\tilde{x}(1)).$$

Thus, she will only sign up if

$$g(x_0 - x^*(1)) \geq [u(\tilde{x}(1), \tilde{y}(1)) - \delta c(\tilde{x}(1))] - [u(x^*(1), y^*(1)) - \delta c(x^*(1))] + h(\tilde{x}(1) - x^*(1)) + \varepsilon, \tag{6.26}$$

where the right-hand side is strictly positive. If Equation (6.13) is not satisfied, then a consumer with $\hat{\beta} = 1$ does not sign up for the program.

Suppose that Equation (6.26) is not satisfied, and that the consumer is aware of a self-control problem ($\beta < 1$). Since $\frac{\partial x^*}{\partial \hat{\beta}} < 1$, then $g(x_0 - x^*(1)) > g(x_0 - x^*(\hat{\beta}))$, so rewards are less attractive when $\hat{\beta} < 1$ (because the consumer anticipates earning fewer rewards due to her tendency to over-consume). Thus, the consumer's motivation for sign-up is driven by the need for self-control when $\hat{\beta} < 1$.

Additional Specifications for the Model Evaluation Section

First, we evaluate the prediction that before enrolling in the program, present-biased consumers are likely to consume more electricity than consumers who are not present-biased. Since there is no unique way of defining consumption before enrollment, we use different specifications in Table 6. Model (I) evaluates the cross-sectional usage in January 2010, Model (II) evaluates the cross-sectional usage in August 2010 (for households who have not enrolled in the program yet), Model (III) uses a weighted average of 2009 consumption where the weights account for the fact that not all households are observed in 2009, Model (IV) looks at all available data before adoption, Model (V) restricts attention to only the 12 months before adoption where this period differs from individual to individual, and lastly, Model (VI) estimates a fixed-effects model of electricity use and then relates the estimated individual effects to the individual specific demographics. Models (IV) to (VI) additionally control for common time effects by including year-month specific indicator variables. The estimated results, which are fairly consistent across the different specifications, suggest that variables associated with present-biasedness tend to have a (weak) positive effect on pre-adoption usage, indicating that present-biased consumers may in fact tend to consume more electricity. This lends credence to these measures as indicators of present-biasedness. Statistically, mean consumption is strongly driven by demographic factors such as household size and income.

Estimating adoption from a retrospective sample

Since our sample is not random, one technical obstacle needs to be overcome in order to consistently perform this analysis. Let $j = 0,1$ denote adoption status and construct a household specific variable T_i, which captures whether household i signed up for the program or not and thus takes the values 0 or 1. In order to model the probability of opting in by household i conditional on observed covariates x_i , $Pr(T_i = j|x_i)$ we need to address the non-random sampling issue first, as our data is sampled conditional on adoption status, a sampling framework that is usually referred to as "choice based sampling" or "retrospective sampling," since it uses the ex-post outcomes as part of the sampling frame. It is well-known in this setting that estimation by maximum likelihood leads to inconsistent parameter estimates (Manski and Lerman 1977). While several approaches are available to address this issue[20], consistent estimates are typically obtained by pseudo-maximum likelihood, where observations are weighted by a factor $\mu_j = n_j/(NPr(T_j))$, where n_j corresponds to the observed sample in group j. N and $Pr(T_1)$ are population parameters denoting the total population of possible adopters and $Pr(T_1)$ the unconditional probability of adoption. However, these quantities are not observed in the sample (we cannot simply assume that the ratio of adopters to non-adopters from a short-run program corresponds to the respective population adoption ratios).

In order to avoid controversies over population priors, we rely on a stronger functional form assumption and assume that $Pr(T_i = j|x_i)$ can be written in a multiplicative intercept form (Hsieh, Manski and McFadden 1985). The logit model is a particular example of the multiplicative intercept form, and thus we assume that:

$$Pr(T_i = 1|x_i) = \frac{exp(c + x_i'\gamma)}{1 + exp(c + x_i'\gamma)}, \tag{6.27}$$

[20] See Amemiya (1985) for a thorough review of this problem and associated classical solutions.

where γ is a parameter vector which measures the extent to which the observed covariates explain adoption. Note that the utility from not opting in is normalized to 0.

An interesting feature of the logit model is that consistent estimates of the β slope coefficients and corresponding standard errors can be obtained even in the presence of choice-based sampling (Prentice and Pyke 1979, Scott and Wild 1986). But the estimated intercept coefficient c is inconsistently estimated and is a function of the unknown parameter μ_1. This imposes some restrictions, as it prevents us from computing marginal effects without imposing out of sample priors on these unobserved parameters.

We first focus on the estimated coefficients reported in panel A of Table 7. The first column reports the coefficients of the logit model in which a user who successfully enrolls in the program is compared to users in the control group. Smaller, more educated households who are concerned for the environment are more likely to opt in. The two variables which most closely proxy for present bias are smoking and dieting. While both groups of consumers are present-biased, the dieting group is more likely to be aware of time inconsistency and the need for commitment, since they seek additional intervention to curb caloric intake. Smoking in itself does not reliably predict the need for commitment, since smokers can include smokers who don't want to quit, those who plan to quit, and those who are actively trying to quit. In the context of the behavioral model's predictions, a more telling indicator would be smokers who buy nicotine patches, whom we cannot identify from the available data. We find that smoking is a significant negative predictor of adoption, while dieting is a significant driver of adoption, suggesting that recognition of present bias is relevant for sign-up. A high loan-to-value ratio is a positive and significant predictor of adoption, while having one or more store credit lines is a negative predictor. Both groups are likely to be present-biased, but given the recent collapse in the housing market and its severity, it is probable that the first group is very much aware of its time inconsistency, as evidenced by previous borrowing behavior. Again, having store credit lines in itself does not indicate demand for commitment, which is the major predictor of sign-up when goals are determined by expectations. To the extent that we believe households have learnt during the recent financial crisis about their financial over-commitment, high loan-to-value ratio may indicate cognizance of present bias.

In the second column of panel A in Table 7, we compare the consumers who opt in with the group of consumers who attempt to enroll in the program but do not succeed. Roughly 1 in 4 users who attempt to enroll fail, typically because they give up during the sign-up process. The results in column 2 do not suggest that present bias is the source of their failure to complete the sign-up process. The most likely explanation is that consumers are required to enter their utility account numbers, which is not readily available to most consumers.

Panel B of Table 7 reports the estimated coefficients of multinomial logit regressions, where the categories correspond to the fractions of committed savings to past usage (0%, 0%-15%, 15%-50%, 50%+). The baseline category consists of consumers in the control group who have not signed up for the program. Looking at the ratios of the coefficients, we see that education is a major driver of setting realistic goals. “Green” consumers and dieters appear to be more likely to choose overoptimistic goals in the range 15%-50%. These patterns in goal selection suggest that goal selection is not completely random.

In Table 8 we explore the choice of goals further. Model (I) estimates a Negative Binomial on the number of chosen actions that the consumers commit to. Education, and in particularly a graduate degree, act as a moderating force on the number of actions committed to by a consumer. Green living predicts a higher number of committed actions, which may indicate that some consumers may select actions they have already done. Model (II) estimates a Tobit model on the fraction of savings relative to past consumption that the consumer selects. Models (III)-(V) and (VI)-(VIII) estimate OLS regressions on the absolute level of goal-implied savings in terms of kWh and dollar savings. The results are very similar. Wealthier households choose higher absolute levels of savings, reflecting their greater savings opportunities. Education continues to act as a moderating influence. Dieting suggests a propensity to overcommit to savings. Since dieters are a group who exhibit a demand for commitment, their behavior is consistent with the model’s prediction that those who recognize that they need commitment and are reference-dependent will set goals to counteract overconsumption. That they tend to be over-optimistic may be not surprising, in light of the fact that dieting itself is often an unsuccessful exercise.

Thus, indicators of demand for commitment predict higher pre-adoption and post-adoption consumption, as well as overly-optimistic goal choices, relative to those who do not exhibit demand for commitment. This evidence is consistent with the predictions of the behavioral model. The EU model assumes away the need for commitment. The only way to reconcile these results with expected utility is to argue that dieting is related to higher consumption both ex post and ex ante, as well as a stronger predilection to sign up for the goals program, while other variables like income do not.

Figure 4: Selecting a goal on the CUB Energy Saver website.

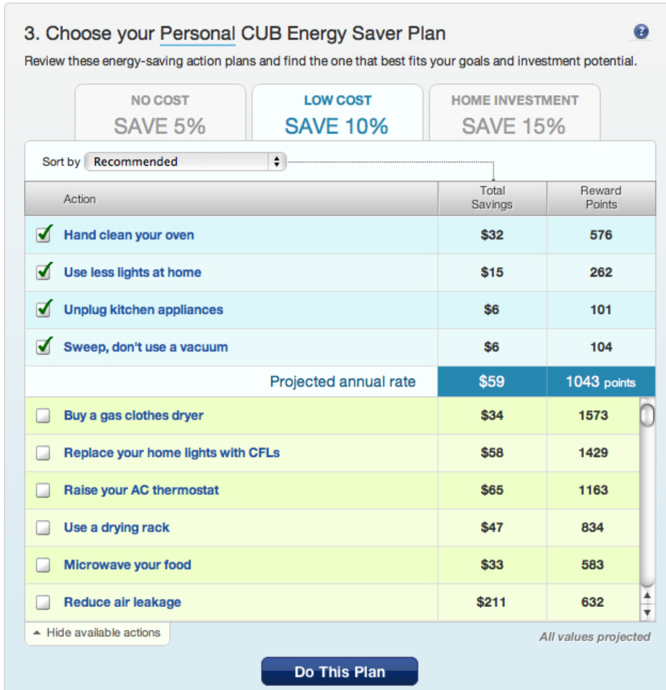

Figure 5: Feedback on historical monthly usage provided on website.

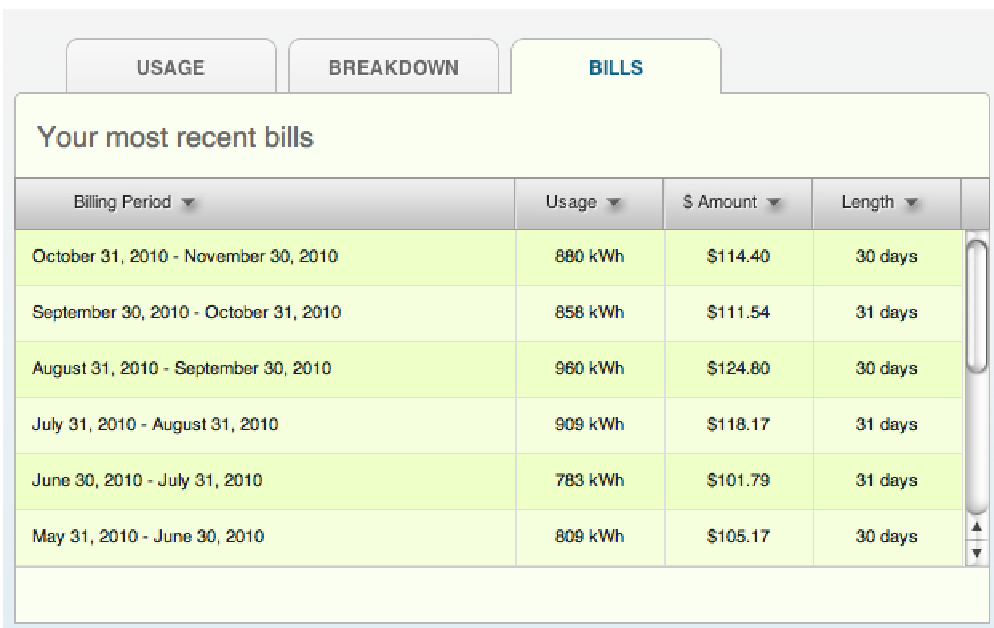

Figure 6: Geographic distribution of adoption in northern Illinois. Green areas indicate zip codes with at least one adopter, and red dots indicate the location of each adopter.

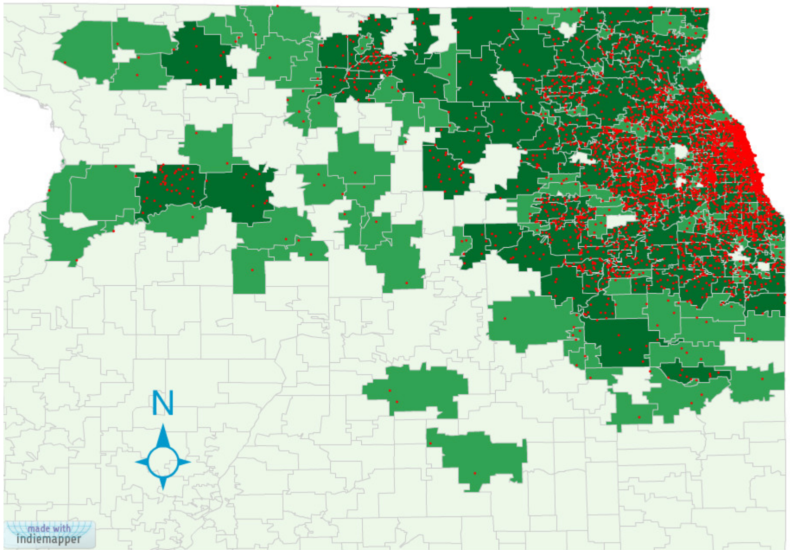

Figure 7: Adoption into the program over time.

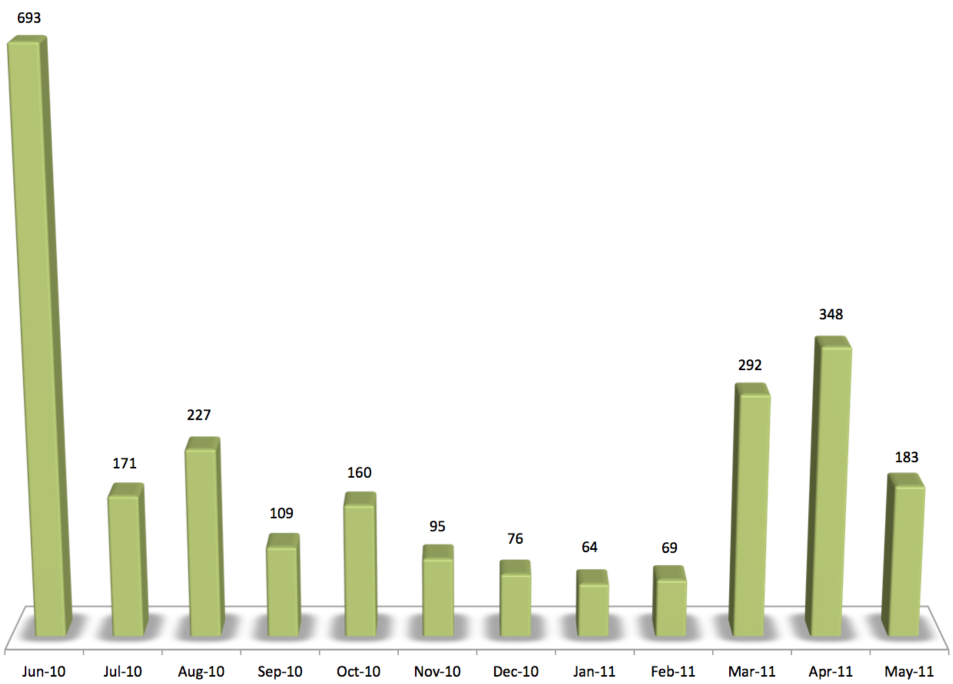

Table 6: Estimation of electricity consumption before program adoption.

log(kwh)	(1) OLS Jan 2010	(2) OLS Aug 2010	(3) GLS 2009	(4) OLS All	(5) OLS 12 months	(6) FE All
Age 35-65	0.0718	0.0732	0.233**	0.0307	0.0472	0.0656*
	(0.0399)	(0.0537)	(0.0831)	(0.0309)	(0.0309)	(0.0303)
Age 65+	-0.00722	-0.115*	0.00660	-0.0763**	-0.0736*	-0.0663*
	(0.0374)	(0.0471)	(0.0588)	(0.0295)	(0.0291)	(0.0298)
HH income 75k-125k	0.159***	0.175***	0.0336	0.163***	0.170***	0.149***
	(0.0319)	(0.0408)	(0.0761)	(0.0249)	(0.0251)	(0.0269)
HH Income 125k +	0.241***	0.308***	0.186**	0.252***	0.248***	0.247***
	(0.0409)	(0.0521)	(0.0626)	(0.0320)	(0.0318)	(0.0326)
College	-0.0199	0.0213	0.0655	0.0179	0.0126	0.0191
	(0.0336)	(0.0431)	(0.0655)	(0.0266)	(0.0265)	(0.0271)
Graduate School	-0.0150	-0.0482	0.0847	0.00539	-0.000237	-0.000540
	(0.0382)	(0.0489)	(0.0829)	(0.0291)	(0.0293)	(0.0310)
Children	-0.0310	-0.00587	-0.00140	-0.0158	-0.00780	-0.0205
	(0.0366)	(0.0438)	(0.0594)	(0.0279)	(0.0284)	(0.0301)
Household Size	0.107***	0.114***	0.104***	0.108***	0.106***	0.109***
	(0.0124)	(0.0146)	(0.0169)	(0.00939)	(0.00945)	(0.0102)
Environmental Issues	-0.0258	-0.0756	0.00837	-0.0503	-0.0473	-0.0423
	(0.0434)	(0.0515)	(0.0774)	(0.0327)	(0.0328)	(0.0363)
Green Living	0.0440	0.0505	0.0586	0.0691*	0.0555	0.0568
	(0.0427)	(0.0476)	(0.113)	(0.0308)	(0.0310)	(0.0335)
Smoker	0.0405	0.118	0.132	0.0711	0.0684	0.0873
	(0.0627)	(0.0776)	(0.0691)	(0.0488)	(0.0487)	(0.0546)
Dieting	0.0110	0.00118	0.0435	0.0255	0.0360	0.0359
	(0.0345)	(0.0404)	(0.0701)	(0.0256)	(0.0257)	(0.0286)
Gambling-Lottery	0.0105	0.0528	-0.0819	-0.00359	0.00608	-0.00636
	(0.0582)	(0.0714)	(0.0911)	(0.0458)	(0.0459)	(0.0544)
Gambling-Casino	0.0694	0.0685	0.108	0.0692*	0.0801*	0.0805*
	(0.0467)	(0.0514)	(0.0737)	(0.0345)	(0.0353)	(0.0402)
Home loan to value 80% or +	0.0671*	0.104**	0.0648	0.0748**	0.0780***	0.0822**
	(0.0296)	(0.0396)	(0.0509)	(0.0233)	(0.0235)	(0.0264)
Credit Line	0.0370	0.0795	0.194**	0.0415	0.0413	0.0371
	(0.0370)	(0.0452)	(0.0707)	(0.0279)	(0.0283)	(0.0278)
Constant	6.070***	6.317***	7.818***	5.715***	5.707***	-0.583***
	(0.0486)	(0.0600)	(0.0975)	(0.0665)	(0.0684)	(0.0334)
Time Effects	-	-	-	Y	Y	-
Observations	2316	1347	2360	52050	28090	2476
R-squared	0.098	0.147	0.143	0.173	0.187	0.154

Standard errors in parentheses, * p<0.05 ** p<0.01 *** p<0.001

Table 7: Conditional logit models of program adoption and level of commitment.

	(A)		(B)			
	Linking against		Adoption by level of commitment			
	Control	Failure	0%	0%-15%	15%-50%	>50%
Age 35-65	-0.258*	0.0599	-0.567*	-0.159	-0.221	-0.499
	(0.131)	(0.127)	(0.226)	(0.173)	(0.129)	(0.265)
Age 65+	-0.700***	-0.169	-0.661***	-0.748***	-0.734***	-0.702**
	(0.0970)	(0.0987)	(0.194)	(0.142)	(0.123)	(0.256)
HH income 75k-125k	0.0871	0.189	0.157	0.0307	0.117	0.0386
	(0.0557)	(0.100)	(0.119)	(0.101)	(0.0745)	(0.161)
HH Income 125k +	0.0187	0.330*	0.247	0.0313	-0.0488	-0.158
	(0.0936)	(0.134)	(0.129)	(0.140)	(0.108)	(0.201)
College	0.323***	0.0970	0.385*	0.391***	0.292***	0.193
	(0.0598)	(0.0788)	(0.153)	(0.0860)	(0.0764)	(0.147)
Graduate School	0.550***	0.0976	0.518**	0.717***	0.458***	0.449*
	(0.107)	(0.0899)	(0.161)	(0.142)	(0.115)	(0.218)
Children	-0.0187	0.124	-0.141	-0.0220	-0.0123	0.268
	(0.0691)	(0.0997)	(0.138)	(0.112)	(0.0879)	(0.167)
Household Size	-0.106***	-0.0283	-0.103*	-0.0419	-0.101**	-0.425***
	(0.0240)	(0.0369)	(0.0488)	(0.0357)	(0.0322)	(0.0677)
Environmental Issues	0.222**	-0.0284	0.117	0.137	0.294**	0.238
	(0.0692)	(0.123)	(0.160)	(0.116)	(0.0961)	(0.197)
Green Living	0.0992	0.132	-0.0103	0.0581	0.169*	0.136
	(0.0608)	(0.107)	(0.136)	(0.125)	(0.0844)	(0.144)
Smoker	-0.265*	0.0877	-0.0223	-0.235	-0.349*	-0.362
	(0.114)	(0.173)	(0.246)	(0.173)	(0.155)	(0.391)
Dieting	0.273***	0.122	0.215	0.146	0.382***	0.297*
	(0.0715)	(0.106)	(0.150)	(0.102)	(0.0871)	(0.140)
Gambling-Lottery	0.106	-0.257	-0.0536	0.174	0.114	0.0307
	(0.110)	(0.144)	(0.246)	(0.173)	(0.146)	(0.299)
Gambling-Casino	-0.0406	-0.00695	-0.165	-0.0906	0.0206	-0.0907
	(0.0802)	(0.119)	(0.197)	(0.135)	(0.101)	(0.192)
Home loan to value 80% or +	0.234***	0.167	0.371**	0.181	0.280**	0.00275
	(0.0710)	(0.113)	(0.116)	(0.0999)	(0.0877)	(0.187)
Credit Line	-0.241**	0.403***	-0.301	-0.0916	-0.283**	-0.311**
	(0.0821)	(0.0830)	(0.187)	(0.111)	(0.0897)	(0.119)
Constant	-0.931***	0.251	-2.561***	-2.401***	-1.895***	-2.025***
	(0.111)	(0.328)	(0.246)	(0.188)	(0.142)	(0.218)
N	12,498	3,680	10,374	10,791	11,035	10,272
Pseudo R-sq	0.035	0.019	0.028	0.027	0.036	0.053

Standard errors in parentheses, clustered as the community level, * p<0.05 ** p<0.01 *** p<0.001

Table 8: Models for the number and degree of savings commitments resulting from goal selection.

	(I) Number of actions	(II) fraction of savings	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
			log(kwh savings)			log($ savings)		
	NegBin	Tobit	OLS	OLS	OLS	OLS	OLS	OLS
	All	All	0%-15%	15%-50%	>50%	0%-15%	15%-50%	>50%
Age 35-65	0.0953	-0.0220	0.0601	0.00389	0.169*	0.0567	0.00428	0.167*
	(0.0542)	(0.0149)	(0.0670)	(0.0429)	(0.0811)	(0.0663)	(0.0429)	(0.0810)
Age 65+	0.0190	0.00867	-0.0224	-0.0321	0.129	-0.0247	-0.0337	0.128
	(0.0537)	(0.0146)	(0.0634)	(0.0419)	(0.0873)	(0.0628)	(0.0419)	(0.0872)
HH income 75k-125k	0.100*	0.00396	0.113*	0.193***	0.187*	0.114*	0.194***	0.186*
	(0.0478)	(0.0132)	(0.0569)	(0.0367)	(0.0815)	(0.0563)	(0.0367)	(0.0814)
HH Income 125k +	-0.0254	-0.0214	0.139*	0.241***	0.208	0.137*	0.239***	0.205
	(0.0582)	(0.0160)	(0.0665)	(0.0459)	(0.109)	(0.0658)	(0.0459)	(0.109)
College	-0.115*	-0.0128	0.0310	-0.00513	-0.148	0.0301	-0.00444	-0.149
	(0.0483)	(0.0133)	(0.0582)	(0.0371)	(0.0803)	(0.0576)	(0.0371)	(0.0803)
Graduate School	-0.217***	-0.0235	-0.0827	-0.0852*	-0.135	-0.0854	-0.0839	-0.132
	(0.0546)	(0.0152)	(0.0648)	(0.0429)	(0.0926)	(0.0641)	(0.0429)	(0.0925)
Children	0.0515	0.0182	0.0595	-0.0154	0.0569	0.0651	-0.0153	0.0542
	(0.0545)	(0.0148)	(0.0613)	(0.0414)	(0.101)	(0.0606)	(0.0414)	(0.101)
Household Size	-0.0119	-0.0206***	0.0255	0.0690***	0.0195	0.0232	0.0696***	0.0206
	(0.0183)	(0.00499)	(0.0205)	(0.0139)	(0.0397)	(0.0203)	(0.0139)	(0.0397)
Environmental Issues	0.100	0.0122	-0.101	-0.00645	0.102	-0.107	-0.00408	0.0988
	(0.0643)	(0.0178)	(0.0781)	(0.0482)	(0.119)	(0.0773)	(0.0482)	(0.119)
Green Living	0.156**	0.0154	0.226**	0.0502	0.134	0.227***	0.0503	0.138
	(0.0599)	(0.0164)	(0.0686)	(0.0461)	(0.108)	(0.0680)	(0.0461)	(0.108)
Smoker	0.0214	-0.0200	0.117	0.0269	0.00774	0.113	0.0273	0.00853
	(0.0958)	(0.0267)	(0.117)	(0.0737)	(0.176)	(0.116)	(0.0737)	(0.176)
Dieting	0.130*	0.0202	-0.0249	0.129***	0.154	-0.0156	0.129***	0.154
	(0.0510)	(0.0140)	(0.0602)	(0.0385)	(0.0887)	(0.0596)	(0.0385)	(0.0887)
Gambling-Lottery	-0.00478	0.00390	0.0284	-0.0271	0.127	0.0340	-0.0294	0.126
	(0.0946)	(0.0265)	(0.114)	(0.0703)	(0.183)	(0.113)	(0.0704)	(0.183)
Gambling-Casino	0.0163	-0.00488	-0.0511	0.111*	-0.107	-0.0479	0.110*	-0.108
	(0.0699)	(0.0196)	(0.0840)	(0.0529)	(0.125)	(0.0832)	(0.0529)	(0.125)
Home loan to value 80% or +	-0.0106	-0.0199	-0.0172	0.0576	0.0391	-0.0152	0.0594	0.0412
	(0.0472)	(0.0129)	(0.0547)	(0.0363)	(0.0886)	(0.0542)	(0.0363)	(0.0886)
Credit Line	0.0527	-0.0251	0.163**	0.00162	0.147	0.160**	0.00254	0.145
	(0.0498)	(0.0136)	(0.0603)	(0.0382)	(0.0801)	(0.0597)	(0.0382)	(0.0801)
Constant	1.626***	0.296***	6.237***	7.177***	7.436***	4.060***	4.986***	5.250***
	(0.0607)	(0.0164)	(0.0742)	(0.0475)	(0.0943)	(0.0734)	(0.0475)	(0.0943)
Observations	2487	2468	790	1034	271	790	1034	271
R-squared			0.066	0.135	0.203	0.067	0.136	0.203

Standard errors in parentheses, * p<0.05 ** p<0.01 *** p<0.001