Success, Failure, and Information: How Households Respond to Energy Conservation Goals

Alastair Fraser*

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Abstract

This paper investigates how households respond to repeated energy conservation goals. I track households' program participation and electricity use decisions across successive annual energy conservation challenges offered by a large electrical utility company. I find that households' decisions whether to re-enroll in the program and attempt a subsequent goal are highly sensitive to their success or failure in achieving their energy conservation goal, but not to the financial incentive to continue participating or to their level of past effort. This suggests that households are either responding to the emotional and normative aspects of success and failure, or are substantially inattentive to information that is provided directly to them. I also find that households' electricity use reduces each year they participate, yet rebounds when they stop participating.

Keywords: Goal-setting, Energy Conservation, Electricity, Financial Rewards, Inattention
JEL Codes: DO4, Q40, Q50, D12, Q48

*School of Economics, The University of Sydney, NSW Australia. Email: alastair.fraser@sydney.edu.au I am grateful to Werner Antweiler, Brian Copeland, and Carol McAusland for their instruction and suggestions. Additionally, I thank Tiho Ancev, Garry Barrett, Patrick Baylis, Valentina Duque, Joshua Gottlieb, Sumeet Gulati, David Kaczan, Thomas Lemieux, Kevin Milligan, Vadim Marmer, Marit Rehavi, Becca Taylor, Vladimir Tyazhelnikov, three anonymous referees and participants at a number of workshops and conferences for their suggestions. I also thank BC Hydro for providing the electricity data and the UBC Centre for Urban Economics and Real Estate for the housing data used in this paper. This work was supported by Environment Canada and Sustainable Prosperity, through the Environmental Economics and Policy Research Network. Declarations of interest: none.

1 Introduction

Many governments and companies use energy conservation and demand-side management (DSM) programs to help customers to modify their electricity consumption or to address environmental externalities. Programs in which participants are repeatedly presented with goals are widespread outside of energy conservation and contain several features: they change incentives by providing financial and/or non-financial rewards for achieving goals, they typically provide information to participants on their progress and/or degree of success, and they often leverage behavioral nudges based on messages of success or failure. While programs that set one-time goals are relatively well-studied, relatively little is known about behaviour in the context of repeated goals, including what drives re-enrollment and how consumers respond to success and failure.

In this paper, I study a long-running energy conservation program called Team Power Smart that repeatedly offered households financial rewards for achieving energy conservation goals. Team Power Smart offered households in the Canadian province of British Columbia the opportunity to attempt annual electricity conservation "challenges" in which a $75 financial reward—equivalent to 11% of the average annual electricity bill—would be provided if they succeeded in reducing their electricity use by 10% compared to the previous year. At the completion of each energy conservation challenge, all households were notified of their degree of energy conservation—their degree of success—directly alongside whether they passed or failed their conservation goal. All households, whether successful or not, were then given the same opportunity to attempt an identical goal of another 10% annual electricity conservation for another $75 reward. This process repeated each year. I observe households' participation and energy use decisions over ten years and as they attempted up to nine separate goals.

This paper has two principle findings that are important to a variety of energy conservation and goal-setting programs. First, I find, that in deciding whether to continue participating, households are highly responsive to their success or failure in achieving a previous goal— but not to their *degree* of success, which affects their financial incentive to re-enroll. Second, I find that energy use declines when households repeatedly re-enroll and partially rebounds as households end their participation, and estimate that re-enrolling causes large additional reductions in energy use.

That success or failure to achieve a goal affects subsequent decisions has been documented in several settings. These include hotel loyalty (Wang et al., 2016) and frequent flyer (Drèze and Nunes, 2011) programs, and the Math Olympiad, in which the decision to continue competing in response to success differs across genders (Buser and Yuan, 2019). However, understanding the underlying mechanisms is frequently complicated by the fact that those who succeed are typically different from those who fail, and succeeding typically creates different subsequent incentives compared to failing. The Team Power Smart design studied here avoids both of these challenges. I take advantage of a natural experiment in which households are as good as randomly assigned success or failure in achieving their energy conservation goal. I find that success increases the probability that a household re-enrolls by 27%. Conditional on success, their degree of energy conservation—which affects the difficulty of achieving the next goal—is uncorrelated with their decision to re-enroll. Importantly, the program design also

provided the same incentive to re-enroll—as well as provided the same information—to both those who failed and succeeded; this substantially narrows the set of mechanisms that can cause such a large responsiveness to success and failure.

That emotional responses can affect decisions is supported by a largely experimental body of literature. This includes findings that negative emotional reactions cause participants to avoid even options they expect will perform better (Ratner and Herbst, 2005), that psychological responses to winning can induce additional effort (Descamps, Ke, and Page, 2018), and that an aversion to future regret and disappointment influences current decisions (Gill and Prowse, 2012). Previous work has also found that people overweight positive relative to negative information about characteristics of importance to them, which has been called the good news-bad news effect (Eil and Rao, 2011) and asymmetric updating (Mobius, Niederle, and Niehaus, 2014). Similarly, people update their beliefs more in response to information that was better than expected (Sharot, Korn, and Dolan, 2011) or confirms rather than refutes their priors (Rabin and Schrag, 1999). People also attribute past success to their ability and a lack of success to factors outside their control (Silver, 1995). The strong responsiveness to success suggested by the present study and the above literature could be important in a wide variety of settings as many, intentionally or not, have elements of achieving goals. For example, households may make energy consumption decisions based on prior 'success' in keeping their energy bill below a previous bill or below an imagined target amount, rather than respond directly to the price, and—in settings where customers can choose between electricity rates and providers—their choices may be driven as much by emotional reactions to bill shock as to the price schedules offered.

An alternative mechanism for households' participation decisions being strongly dependent on past success or failure, rather than on the future incentive offered, is that they may be inattentive to information (Gabaix, 2019). Because each energy conservation goal is an additional 10% compared to the previous year, a household's prior degree of success affects the incentive to re-enroll. Despite this, I find households largely take into account only their success or failure and not their degree of success, which suggests that households may use simple heuristics in making decisions, such as using the binary of success or failure, while being inattentive to the detailed information provided. Such inattention is consistent with previous findings. Within the energy use literature, evidence suggesting inattention includes that consumers temporarily use less electricity after receiving a bill (Gilbert and Graff Zivin, 2014) and use more after enrolling in automatic bill payments (Sexton, 2015). Consumers do not pay close attention to energy efficiency labels (Sallee, 2014; Houde, 2018; Allcott and Taubinsky, 2015) or residential energy efficiency (Palmer and Walls, 2015), and may not be attentive to marginal electricity prices (Ito, 2014; Shaffer, 2020). Similar evidence of inattention comes from the closely related setting of water consumption, for which both billing frequency and perceived prices affect consumption (Wichman, 2014; Wichman, 2017). In addition to inattention and emotional responses affecting decisions, the general mechanisms through which consumers respond to information are important for further study, as information provision is widely used to modify electricity consumption (Gans, Alberini, and Longo, 2013; Jessoe and Rapson, 2014; Schleich, Faure, and Klobasa, 2017; Martin and Rivers, 2018; Byrne, Nauze, and Martin, 2018; Stojanovski et al., 2020).

While self-selection is inherent in decisions on repeating goals, it also creates concerns that energy conservation may be credited to Team Power Smart and rewards may be paid to participants for changes in energy use that would have happened even in the program's absence. As Boomhower and Davis (2014) show, this non-additional conservation can be large in energy conservation programs, but is difficult to estimate. I address the identification challenge created by self-selection in Team Power Smart by employing both fuzzy regression-discontinuity and event-study empirical strategies.

To estimate the causal effect of a second conservation challenge, I exploit the discontinuity in re-enrolling created by success and failure. Using a fuzzy-regression discontinuity design, I find that attempting an additional conservation goal causes large additional reductions in energy use. I also use an event study model to estimate the short-run reductions and long-run persistence of electricity use changes. I find that an initial conservation goal is associated with an immediate 4.9% average reduction in electricity use that lasts throughout the twelve months of the initial challenge; an important caveat is that, due to self-selection, the event-study estimates are an upper bound on the causal treatment effect. However, while electricity use continues to decline among households that re-enroll, it partially rebounds as households end their participation in the program. These descriptive event-study estimates are consistent with the fuzzy-regression discontinuity estimates and support the conclusion that households tend to make short-run adjustments in addition to permanent investments or creating persistent habits, and that the ongoing incentive of additional goals is important for long-run lower electricity

The rebound in energy use contrasts with the findings of Ito (2015) and Harding and Hsiaw (2014) who both study energy conservation goal–setting programs with features in common to this setting.[1] Ito (2015) investigates a mandatory program offering customers an additional 20% discount on their bill if they achieved a 20% reduction over four months, and Harding and Hsiaw (2014) studies a voluntary program in which customers voluntarily choose energy conservation goals without a financial reward. Ito (2015) does not find any long-run rebound over subsequent years, but does find that results are driven by higher air conditioner use in warmer areas, whereas I find energy conservation occurs in both seasonal heating and base load electricity use. Harding and Hsiaw (2014) finds some evidence of an immediate rebound along with persistent reductions over the following 18 months for customers who choose realistic conservation goals. These differing results suggest that whether households respond to conservation goals and financial rewards with persistent reductions may depend on the way electricity is used within a home, or on the program design and context in which it is offered—for example, a mandatory program during an electricity crisis, as in Ito (2015), or a repeated voluntary program as part of routine electricity use, as in this paper.

This paper's finding of continued reductions in electricity use when households re-enroll, and a rebound when they don't, is similar to the "action and backsliding" found by Allcott and Rogers (2014) in households' responses to repeated home energy reports. The rebound and large effect of success on the decision to continue suggests an important trade-off in repeated goal-setting programs: more difficult

[1] A number of other papers have also considered financial rewards and goal setting in the context of energy conservation, though with less overlap to the setting studied here (Winett et al., 1978; McClelland and Cook, 1980; Midden et al., 1983; Houwelingen and Raaij, 1989; Abrahamse et al., 2007; McCalley and Midden, 2002; Mizobuchi and Takeuchi, 2012; Dolan and Metcalfe, 2015; Gerard and Costa, 2015).

goals can induce more effort (Gutt, Rechenberg, and Kundisch, 2020), but at the cost of higher failure rates and lower subsequent participation.

The remainder of this paper is organized as follows. Section 2 describes the institutional setting, design of the Team Power Smart electricity conservation program, and data. Section 3 gives an overview of the two empirical approaches used in this paper. Section 4 describes the event study results. Section 5 explores households' decisions whether to leave the program and presents the fuzzy-regression discontinuity results. Section 6 concludes.

2 Institutional Setting, Program Design, and Data

BC Hydro is Canada's second largest integrated electrical utility company. It serves 1.7 million residential customers covering 95% of the population in British Columbia (BCH, 2014a). As part of government mandated improvements to energy efficiency, BC Hydro launched a voluntary program—Team Power Smart—summed up by the promotion: "*Looking to save money on your electricity bills? Become a member of Team Power Smart and challenge yourself to reduce your home's electricity use by 10% in the next year. If you're successful, you can earn a [$75] reward*" (BC Hydro, 2017).

Enrolling in the program requires only the minimal time cost of registering online. The program consists of energy conservation challenges that require households to reduce their aggregate electricity use over a 12-month period by 10%. Because it is the aggregate annual conservation that matters for success, households can miss their 10% goal in any given month and still pass their challenge. Households can start a challenge in any month of the year, as long as they have 12 months of electricity use in their current home to establish their baseline. All participants can view their progress towards their conservation goal through the BC Hydro website and can access a variety of tips and suggestions for reducing their electricity use. The online account provides households with feedback on their electricity use as well as monthly and cumulative progress towards their annual 10% conservation goal.

Each household's annual 10% conservation goal is measured relative to its own annual electricity use over the preceding 12 months. To avoid unduly penalizing or rewarding households for changes in weather instead of their energy conservation effort, BC Hydro applies a weather adjustment algorithm. This algorithm adjusts the previous year's electricity use (from which the 10% reduction goal is measured) for annual changes in heating degree days (HDDs). As a result, the percent reduction in electricity use that is displayed to households—and that they receive credit for—differs from the actual percent change in kilowatt hours (kWh) they use and are billed for. I refer to changes in actual electricity use, prior to their weather-adjustment, as 'billed changes'; all event-study and fuzzy-RD estimates are of billed changes. I refer to the changes in electricity use that are displayed to households as 'credited changes.' Households would have had to calculate their own annual percent change in electricity use to notice that their credited percent reduction differed from their reduction in billed electricity use. I discuss the online portal, weather adjustment, and differences between billed and credited changes in detail in Appendix A.

Upon completing the 12 months of the challenge, BC Hydro applies the final weather adjustment, accounts for bi-monthly billing and any idiosyncratic factors, and evaluates whether the household has passed or failed their challenge. While the conservation goal advertised to customers is 10%, BC Hydro evaluates final success or failure against a 9.5% conservation threshold. Households that reduced their credited electricity use by greater than or equal to 9.5% pass their challenge while the rest fail. As I discuss further in Section 5, the way BC Hydro notifies households is important: everyone was required to "*[l]og in to MyHydro to get your results. If you've reached your goal, choose how to receive your reward: a mailed cheque or a credit on a future bill.*"[2] As a result, both successful and unsuccessful households must log in to the online portal to learn whether they succeeded, and they receive the same information on their degree of electricity conservation alongside their status of success or failure.

2.1 Structure of Additional Conservation Challenges

A novel feature of Team Power Smart is that households that both pass and fail their challenge are given the same option to start a subsequent conservation challenge for another $75 rebate. Each subsequent challenge follows the same process as the initial conservation challenge. Households can decide to undertake another 10% conservation goal based on their previous 12 months of (weather adjusted) electricity use. The new reduction goal is independent of whether the prior 12 months contained a challenge or not, and independent of whether the prior challenge ended in success or failure. The baseline for a household immediately starting an additional challenge would be the 12 months of the just completed challenge, while a household waiting four months before starting their next challenge would have a baseline set by the average of their last eight months of their previous challenge and the four month gap prior to starting their next challenge. Because each additional 10% conservation challenge is evaluated relative to the prior 12 months, the reduction in electricity use achieved by a household during a challenge affects their incentives on when and whether to undertake a subsequent challenge. Under the reasonable assumption of increasing marginal costs to electricity conservation, the greater the conservation achieved during a challenge, the greater the incentive to postpone a subsequent challenge or leave the program.

2.2 Data and Household Characteristics

Under a non-disclosure agreement with BC Hydro, I obtained an anonymized balanced panel of monthly billed electricity use and program participation histories from January 2006 to December 2015 for a sample of 10,000 Team Power Smart program participants and 20,000 non-participants. By comparison, 19,905 households—or 1.2% of all households served by BC Hydro—participated in an energy conservation challenge in 2012 alone (BCH, 2014b). While rationally (and if well-informed) overall participation rates should be much higher as the time costs of participation are minimal, I do not draw conclusions from the initial program enrollment rates, as it is not known to what degree people were aware of the program. I combined these records with detailed individual building characteristics

[2] Participation in the program by the author and conversations with BC Hydro.

from the property assessment corporation, BC Assessment.[3] The samples of participants and non-participants were randomly selected from the population of program participants and non-participants in the Greater Vancouver Area (an urban and suburban population of 2.4 million) who had not moved over the ten years of the panel. In comparison, on average 69% of people in this area moved in the previous five years (Statistics Canada, 2016). As a result, both participant and non-participant samples represent more stable households than average in the population.

Comparing the non-participants in the sample to all residential units from the Greater Vancouver Area indicates that these relatively stable households are, unsurprisingly, more likely to live in single-family dwellings and less likely to live in apartments or townhouses (Appendix Table A.2). Comparing similarly stable participants and non-participants indicates that participants are more likely to live in apartments or townhouses compared to single-family dwellings, and are more likely to use primarily non-electric heating (Table 1). However, differences in participation rates cannot be attributed solely to different propensities of selecting into the program among household types. This is because BC Hydro engaged in a range of advertising for Team Power Smart, such as on bus shelters and online, that is unlikely to have been uniformly noticed by different household types and thus affects their likelihood of becoming participants.

The average monthly electricity bills among participant households is $58, meaning that the $75 reward is equivalent to 10.7% of the annual electricity bill and is in addition to their bill savings (Table 1). Participating households tend to have slightly higher electricity use than similar non-participant households in the pre-program year of 2006 (Table 1). After controlling for heating-building type, the monthly average electricity use among participant households is 15 kWh (t statistic 2.76), or 1.5%, higher than non-participants—estimates in Appendix A.2.

2.3 Outcomes During Multiple Conservation Challenges

Table 2 summarizes the decisions and outcomes of participant households across multiple conservation challenges. During the initial three challenges, 60–62% of households decided to re-enroll in an additional challenge; this probability mechanically declined among later challenges due in part to the limited panel length. Consistent with an increasing difficulty of achieving additional reductions in electricity use, the unconditional probability of passing a conservation challenge declines with additional challenges. Households are more likely to re-enroll in another challenge if they pass, rather than fail, their current challenge. In contrast, households are less likely to pass their next challenge if they passed their previous challenge. This pattern matches the incentive structure previously discussed; passing a challenge requires achieving the 9.5% conservation threshold, which makes passing the next challenge harder compared to not achieving the initial goal. In Appendix A.3 I find no evidence that households strategically chose their subsequent conservation challenge start date or sign up after periods of unusual weather.

[3] BC Assessment data was provided by the University of British Columbia Centre for Urban Economics and Real Estate.

Table 1: **Household Characteristics**

	Participants % of total	Non-Participants % of total	Mean Difference in kWh	(t-statistic)	as %
Electric Heating and:					
1 Story Single Family Dwelling	6.3	13.7	40.2	1.6	2.8
2 Story Single Family Dwelling	4.1	8.2	62.5*	2.0	4.1
1.5 Story Single Family Dwelling	1.1	2.3	89.2	1.5	6.3
Apartment	11.7	7.8	6.3	0.5	1.2
Townhouse	5.1	4.1	30.8	1.2	3.0
Other	0.8	1.8	40.6	0.6	3.1
Non-Electric Heating and:					
1 Story Single Family Dwelling	27.9	27.5	25.8**	2.8	3.1
2 Story Single Family Dwelling	15.4	12.0	-53.8***	-3.8	-6.0
1.5 Story Single Family Dwelling	2.7	2.6	60.8*	2.1	7.3
Apartment	2.6	1.6	19.5	1.2	5.9
Townhouse	6.6	4.2	63.8**	4.4	11.6
Other	1.8	2.5	26.4	0.9	3.6
Unknown Heating	13.7	11.8	-4.9	-0.3	-0.5

	Participants		Non-Participants	
	Mean	SD	Mean	SD
Monthly kWh	884	568	972	636
Average Monthly Bill	$58		$64	
Property Value ($1,000)	$672	$465	$731	$579
Floor Area (Square Feet)	2025	977	2123	997
Number of bedrooms	3.37	1.25	3.55	1.3
Total Households	9,818		19,250	

Notes: % of total is the percent of participant and, separately, non-participant households by heating-building type. *Difference* shows the mean difference in pre-program (2006) electricity use between participant and non-participant households within each heating-building type category. (*t-statistic*) is on the difference in mean kWh between participants and controls. *as %* is the mean difference as a percent of non-participant electricity use within each heating-building type category. SD = standard deviation.

Table 2: **Probability of Challenge Outcomes**

Challenge number	Households in Challenge	**Probability of Re-Enrolling** All	if Failed Challenge	if Passed Challenge	**Probability of Passing** All	if Failed Previous. Chal.	if Passed Previous. Chal.
1	8,877	0.62	0.55	0.77	0.34		
2	5,531	0.60	0.56	0.71	0.31	0.33	0.29
3	3,346	0.60	0.56	0.71	0.28	0.30	0.24
4	2,014	0.54	0.51	0.64	0.26	0.28	0.23
5	1,091	0.46	0.41	0.60	0.24	0.27	0.17
6	498	0.38	0.36	0.44	0.24	0.25	0.21
7	188	0.27	0.26	0.28	0.29	0.28	0.31
8	50	0.12	0.07	0.33	0.18	0.20	0.13
9	6	0.00	0.00	0.00	0.33	0.33	0.33

Notes: Households in Challenge is the number of households undertaking their first, second, etc., challenge. *Probability of Re-Enrolling* is the probability of re-enrolling in a subsequent conservation challenge, conditional on being in the current challenge. *Probability of Re-Enrolling if Failed [Passed] Prev. Challenge* is the probability of re-enrolling conditional on failing [passing] the current challenge. The *Probability of Passing* is for a household's current challenge, while the *Probability of Passing if Failed [Passed] Prev. Chal.* is the probability of passing the current challenge conditional on the fail or pass status of the previous challenge.

3 Empirical Strategies

There are two principal challenges to estimating the causal effect of an energy conservation challenge. First, households may self-select into Team Power Smart based on shocks to their past electricity consumption or expectations of their future consumption, perhaps responding to unexpectedly large bills or taking advantage of anticipated reductions in their electricity use because of, for instance, the purchase of an efficient appliance. Second, all households have the option of re-enrolling in additional conservation challenges. This makes the persistence of energy savings and the causal effect of subsequent conservation challenges dependent on households' decisions to select into additional challenges. To address these challenges, I employ two empirical strategies. In Section 4 I first use an event study research design to estimate the monthly average changes in electricity use associated with participation in Team Power Smart (Angrist and Pischke, 2008). After describing these patterns of energy use, I then study the re-enrollment decision and estimate causal treatment effects in Section 5 using a fuzzy Regression Discontinuity (RD) design (Lee and Lemieux, 2010) and the discontinuity in the probability that households continue to a second conservation challenge.

4 Event Study Empirical Strategy

I estimate two closely related event study models. The first is a standard fully saturated event study model:

$$y_{it} = \sum_{\tau=-119}^{108} \beta_\tau D_{it,\tau} + \alpha_i + d_t + \epsilon_{it} \tag{1}$$

where y_{it} is the log of monthly electricity use for individual i in month-of-sample t, α_i is an individual fixed effect, and d_t is a month-of-sample fixed effect. $D_{it,\tau}$ is a dummy variable equaling 1 if individual i in month-of-sample t began treatment τ months previously, with $\tau = 1$ the month-of-sample a treated household undertakes its first conservation challenge. In my main specifications I include a control group of non-participant households who are never treated and therefore have $D_{it,\tau} = 0 \,\forall\, \tau$. I set the second year before each households initial conservation challenge as the baseline year by defining $D_{it,\tau} \equiv 0 \,\forall\, \tau \in [-12..23]$; this allows important trends in the 12 months preceding participation in the program to be estimated. β_τ are the non-parametric changes in electricity use relative to the baseline for τ months lag or lead of treatment and cover all periods in the panel.

Comparing estimated $\hat{\beta}_\tau$ across households that undertake different numbers of conservation challenges sheds light on both the process of self-selection into additional challenges and the persistence of energy savings. However, households were not required to immediately start a subsequent conservation challenge: some households undertaking multiple conservation challenges have a gap in time between when their previous challenge was completed and when they re-enrolled in a subsequent challenge. To account for this variable gap in time, I modify the event study model in two ways. First, I include the indicator $G_{itg} = 1$ if household i in month-of-sample t has completed challenge g but has not yet re-enrolled in challenge $g + 1$. Second, the months between challenges which define $G_{itg} = 1$ are not counted when measuring the event-time τ. This defines $D_{it,\tau}$ equal to 1 if individual i in month-of-sample t began treatment τ months previously where τ months are either active challenge months or are months after a household has ended their participation in the their last challenge. As a result, all months are covered by the mutually exclusive indicators G_{itg} and $D_{it,\tau}$ (except for the excluded baseline period) and the modified event-study model is fully saturated with all possible lags and leads,

$$y_{it} = \sum_{\tau=-119}^{108} \beta_\tau D_{it,\tau} + \sum_{g=1}^{8} \theta_g G_{itg} + \alpha_i + d_t + \epsilon_{it} \tag{2}$$

G_{itg} is not necessary for estimating an event study model on this data; instead, it simplifies the interpretation of $\hat{\beta}_\tau$ across households with variable gaps between their challenges. For example, for households ending their participation after a single challenge $\hat{\beta}_\tau, \tau = [13..24]$ are the estimated changes in electricity use for the first 12 months immediately following their initial challenge. For a household that immediately re-enrolls in a second challenge $\hat{\beta}_\tau, \tau = [13..24]$ are the estimated changes in electricity use for the twelve months of the second conservation challenge. For a household that waits two months before re-enrolling, $\hat{\beta}_\tau, \tau = [13..24]$ are still the estimated changes in electricity use for the twelve months of the second conservation challenge while $\hat{\theta}_g, g = 1$ is the estimated change over the two month gap between that household's 1st and 2nd challenges. In my preferred specifications, I

pool all households that re-enroll within 12 months of completing their previous challenge and exclude households with longer gaps between challenges; results are robust to excluding shorter and longer gap lengths.

4.1 Event Study Estimates

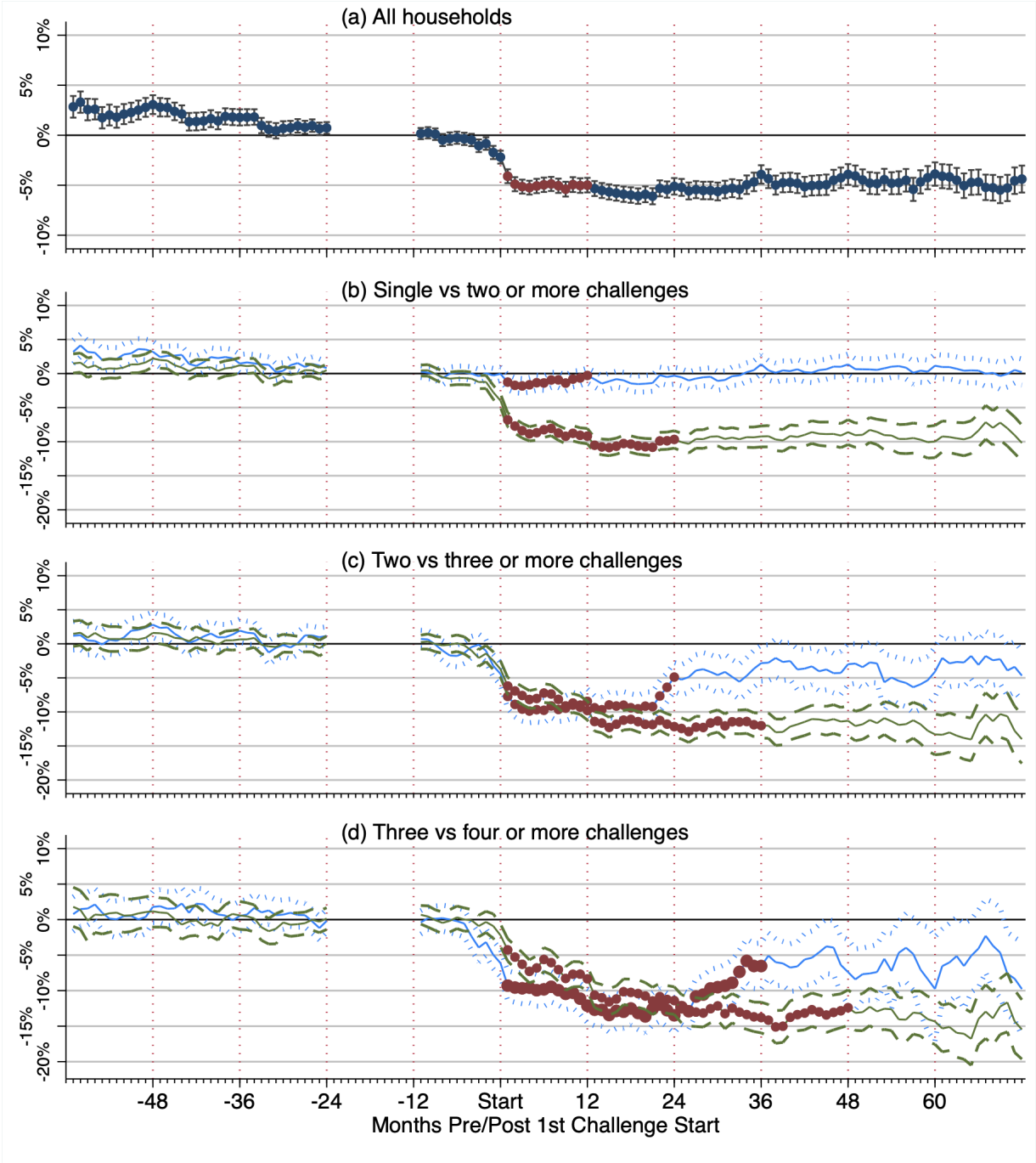
At the end of every challenge, households decide whether to end their participation or re-enroll in a subsequent challenge. Event-study estimates of, for example, households that complete at least a second challenge include both households that ended their participation and households that re-enrolled in a third challenge: this averages any potential rebound in electricity use among those that ended participation with any additional treatment effects from a third or subsequent challenge undertaken by the re-enrolling households.

To separate the effects of ending participation from re-enrolling, Figure 1 presents event-study estimates for households depending on how many challenges they participate in. In panel 1(a) I estimate equation (1) pooling all participant households regardless of how many times they re-enroll. Estimates $\hat{\beta}_\tau$, $\tau > 12$ in panel 1(a) are the average change in electricity use across both households that ended their participation after the initial challenge, and households that re-enrolled. In panels (b), (c), and (d), I estimate equation (2) separately for households that respectively decide whether or not to re-enroll after a first, second, and third conservation challenge. Each panel shows the estimates for two mutually exclusive groups (end participation versus re-enroll) which combined are the re-enrolling households from the previous panel.

The pre-treatment estimates in Panel 1(a) are non-zero and suggest a potential violation of the parallel trends assumption. Estimates for the twelve months of the initial conservation challenge then show a substantial reduction in electricity use of 4.9% relative to the second year pre-treatment baseline. However, self-selection into participation could bias estimates even in the absence of a pre-treatment trend. Of particular concern is if households make an energy efficiency investment like purchasing a new appliance and sign up for Team Power Smart as a result; given the voluntary nature of the program, such self-selection biases cannot be ruled out. While self-selection could bias estimates upward or downward, I consider the estimated energy conservation to be an upper bound on the causal treatment effect. I do this to be cautious and as it is more likely that households would self-select into the program to take advantage of the $75 reward rather than disadvantage themselves by self-selecting into participation if their electricity use would otherwise be increasing.

Panel (b) shows that the non-zero pre-treatment estimates arise among households that participate in a single conservation challenge and do not re-enroll, and are largely not present in estimates for households that do re-enroll. Panel (b) also shows that households that end their program participation after their initial challenge have average reductions during the challenge of only 1.2%, while those that re-enroll in a second challenge reduce their use by 7.2% during their first challenge. This suggests self-selection into a second challenge based on their initial electricity conservation. Alternatively, it could be that households which are ex-ante likely to continue to additional conservation challenges are also those

Figure 1: Event study estimates



Notes: Estimated $\hat{\beta}_\tau$ with 95% confidence intervals from equation (1) for panel (a) and equation (2) for panels (b)-(d). The start of the first challenge begins in the month labelled *Start*. The visual gap in estimates between months $\tau = -12$ and $\tau = -23$ is the excluded baseline year. Panel (a) pools all households regardless of the number of challenges undertaken; estimates for the period after the initial challenge ends ($\tau > 12$) contain both households ending participation and those that re-enroll. Panel (b)-(d): Estimates in blue are households that end participation after the given challenge and estimates in green are for households that re-enroll. Red dots mark months in which a household has undertaken a challenge; subsequent months (in green) that may include additional challenges are not marked with red dots. The estimation samples are limited to households that, if they re-enroll, do so within 12 months of completing their initial challenge. Not shown are estimates θ_g for electricity use during the gap between the first and second challenges. This aligns months for households that end their participation with months for households that re-enroll. Estimates include individual and month-of-sample fixed effects. I cluster standard errors at the household level. See Appendix H for all point estimates.

households that achieve large reductions in energy use.

Panels (c) and (d) show a similar pattern; both households that decide to end their participation after the challenge and those that decide to re-enroll have similar changes in electricity use leading up to and during the challenge. Households that end their participation show a rebound in their use over the final months of the challenge: those that re-enroll show continued reductions. These patterns suggest that households that don't re-enroll stopped making conservation efforts prior to the end of the challenge. This rebound does not return electricity use to pre-program levels as it remains approximately 6.5% lower than pre-program levels.

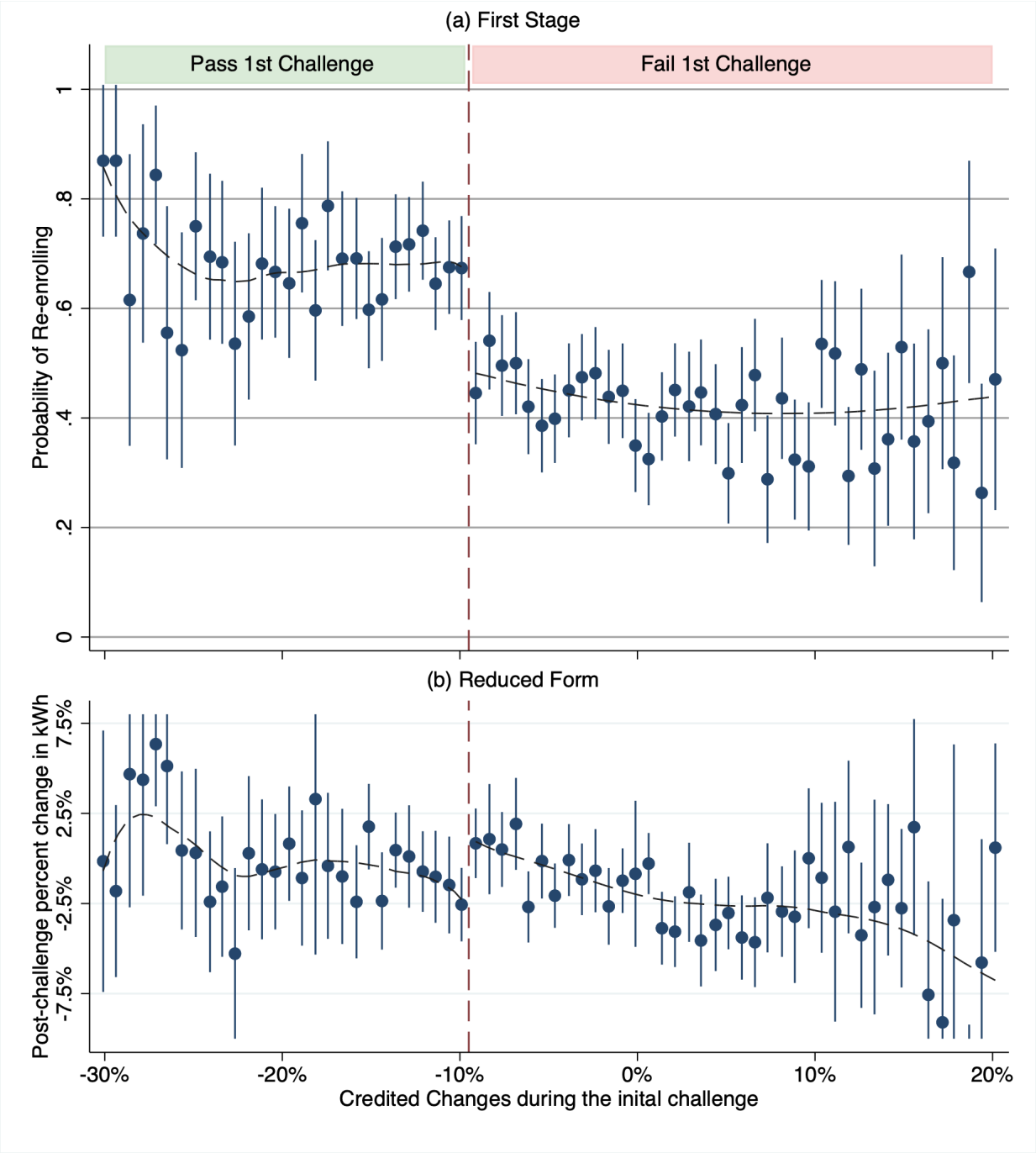
The pattern of energy conservation in Figure 1 is informative of potential sources of self-selection. I consider these in Appendix B, along with a series of robustness checks of including all non-participant households, using other baseline periods, and excluding never-treated control households. I now turn to the main focus of the paper—re-enrollment in an additional conservation challenge.

5 Success versus Failure and Re-enrollment

Section 4 documented how electricity use diverges between those who decide to leave Team Power Smart and those who decide to re-enroll in an additional conservation challenge. This suggests that the decision to re-enroll is important as energy use may rebound in the absence of subsequent program participation, and that additional conservation challenges could cause additional reductions in electricity use. In this section I study two aspects of households' re-enrollment decisions: the decision to attempt a subsequent goal in response to success-versus-failure, and causal reductions in electricity use from continuing to a second conservation challenge.

Before discussing mechanisms, it is helpful to see the discontinuity. Figure 2 plots the probability of re-enrolling in a second challenge against the credited changes in electricity use from a household's initial conservation challenge. Among households that fail their initial challenge, their probability of continuing to a second challenge is largely independent of their credited changes in electricity use. Figure 2 shows that households with large increases in electricity use of around 20% have a similar probability of re-enrolling as households that nearly achieved their 10% reduction goal. A similar pattern is seen amongst households that passed their challenge; those that barely pass with reductions of ∼10% are equally likely to continue as households that achieved reductions of ∼20%. In contrast, there is a sharp discontinuous jump in the probability of continuing to a subsequent challenge at the 9.5% threshold for success. This pattern shows that, in deciding whether to continue in the program, households are responsive to their success or failure in a conservation challenge, but are largely insensitive to the level of reductions in electricity use that they are credited with or achieve. Importantly, this discontinuity occurs only at the 9.5% threshold—which households did not expect—and not at the 10% goal households expected and were trying to achieve or in their billed electricity use (Appendix D). While similar discontinuities in credited changes exist after the second and subsequent conservation challenges, the sample is too small for instrumental variable estimates.

Figure 2: **Discontinuities in Re-Enrolling and Subsequent Electricity Use**



Notes: Credited changes are the annual changes in electricity consumption displayed to households. The vertical dashed line indicates the 9.5% threshold defining success; households to the left of the dashed line pass their conservation challenge while those to the right fail. Panel (a): The mean probability of re-enrolling with 95% confidence intervals among households within 0.75% width bins in credited changes. Panel (b): The mean change in billed electricity use in the first year after the initial conservation goal. The dashed line is a first order local polynomial fit; this is to clarify the local trends and is not the fuzzy RD fit.

The magnitude of the discontinuity in Figure 2 is large compared to differences in re-enrollment probability across household characteristics. To explore what correlates with households' re-enrollment decisions, I estimate several Probit models—details in Appendix D. These show that a households pre-determined characteristics have little direct, or in-direct through level of electricity conservation, correlation with the probability of re-enrolling. Taking the largest difference in point estimates for the probability of re-enrolling across characteristics finds townhouses are 8.6 percentage points more likely to re-enroll than homes classified "other," and households with pre-program electricity use three standard deviations above the mean 2006 use are 5.9 percentage points more likely to re-enroll. In comparison, households that just pass their conservation challenge are 14.5 percentage points, or 27%, more likely to re-enroll than if they just fail.

5.1 The response to success or failure

Why does success or failure in achieving a goal have such a large persuasive/dissuasive effect on the decision to re-enroll? The specific design of the Team Power Smart energy conservation goals helps to clarify potential mechanisms. The inability to precisely manipulate energy conservation, the weather adjustment, and the ex-ante unexpected 9.5% threshold all contribute to households being as good as randomly assigned into success and failure. Comparing households that just failed to those that were slightly more successful and therefore just passed allows otherwise identical households to be compared; this rules out differences in re-enrollment being due to differences in characteristics like effort or ability. As discussed previously, the $75 reward offered for another 10% reduction does not depend on prior success or failure. Conditional on their previous years electricity conservation, households face the same incentives to re-enroll independent of past success or failure. Importantly, households were notified when their energy conservation challenge was completed, but were not informed of their success or failure until they logged into their online account. Once logged in, households received their final success or failure status directly alongside their degree of credited energy conservation; successful and unsuccessful households were equally aware of their degree of success. Combined, these features created a remarkably clean natural experiment: the large discontinuity in the decision to re-enroll from Figure 2(a) is not due to different households types, different incentives, or different information being provided to those who pass as opposed to those who fail. This suggests that *how* success or failure, and the degree of success, is interpreted is critical to their decision whether to re-enroll.

Mechanisms underlying responses to success or. failure can be broadly separated into the use of information communicated by success and failure, and psychological responses to its emotional and normative aspects. In deciding whether to re-enroll, the degree of success or failure in a previous goal is objective information from which people can update beliefs about their ability and the goal's difficulty. The large psychology literature on goal-setting finds that self-efficacy, which is the belief in one's ability to affect outcomes, can be altered by information on success and failure, and this in turn influences goal commitment and effort (Gutt, Rechenberg, and Kundisch, 2020; Soman and Cheema, 2004; Locke and Latham, 2002; Bandura and Locke, 2003). However, as households observe their degree of success—their energy conservation—the binary of success versus failure does not itself convey additional

information, and a fully informed rational agent would not respond discontinuously. It is well known that consumers may be inattentive to information or find understanding its implications too mentally costly to consider—see Gabaix (2019) for a review of behavioral inattention. An inattentive household may update their beliefs about whether they'll succeed in another goal based on a simple heuristic that previous success implies future success, and past failure implies future failure. While inattention has been studied in a wide variety of contexts, including energy use (Allcott, 2011; Sallee, 2014; Allcott and Taubinsky, 2015; Davis and Metcalf, 2016), inattention to information as an explanation for responses to success or failure does not appear to have been directly studied in any setting.

How people interpret information can also be affected by the emotional and normative aspects of information. As Eil and Rao (2011), Peysakhovich and Karmarkar (2016), and Mobius, Niederle, and Niehaus (2014) show, 'good' news can have a larger effect on decisions than 'bad' news, which leads to asymmetrical responses. Such asymmetrical updating could cause the observed discontinuous response if households update their beliefs, such as a belief in their ability to reduce their energy use vis-à-vis the costs of doing so, more strongly in response to the good news of success than the bad news of failure. This is consistent with Eskreis-Winkler and Fishbach (2019) who find people answering simple binary choice questions learn less from prior failure than prior success, even when it was more cognitively taxing to learn from their prior success. That success and failure are not viewed in purely objective terms is supported by Medvec, Madey, and Gilovich (1995), who show that Olympian bronze medal winners are happier than those winning silver; their explanation is that satisfaction is determined more by what the Olympian envisions as the counterfactual outcome rather than their objective place on the podium.

Psychological responses to the emotional and normative aspects of success and failure may also directly affect subsequent decisions. A discontinuous response to success versus failure may arise if households face a higher emotional cost from a second failure than from an initial failure, leading to those that initially fail being less likely to re-enroll than those who initially succeed, even if they have identical beliefs about their likelihood of subsequent success. Gill and Prowse (2012) consider disappointment aversion, in which where agents are loss-averse around an endogenous expectations-based reference point that is determined through competition with a rival. If households are similarly disappointment averse, they may adjust their reference point—separate from an updated belief about future success—in response to success and failure. This may lead them to avoid re-enrolling in order to avoid the cognitive cost of greater future disappointment. Work on regret aversion by Marcatto, Cosulich, and Ferrante (2015) finds that experiencing regret directly inhibits people from choosing the same option a second time "even when it is still objectively the best alternative." Extensions of prospect theory to dynamic decision making (Tymula et al., 2021) and a large literature on reinforcement learning theory (Rangel, Camerer, and Montague, 2008) offer alternative theoretical frameworks for describing how past outcomes like success and failure may affect the subsequent decisions.

A remaining potential explanation is that the $75 reward received has a direct effect on the decision to re-enroll by altering a household's budget constraint. However, if a $75 income shock made a material difference to re-enrollment, then presumably re-enrollment would also change with household income.

I do not find that the probability of re-enrolling differs across property values or floorspace size, which I assume to be correlated with household income (see Appendix D). While $75 is a small reward relative to the median provincial household income of $80,000, it may have a larger effect if households use mental accounting and consider the $75 as part of an energy category rather than aggregate income. While theorized, mental accounting in energy use has not been demonstrated (Hahnel et al., 2020). Households would also have to direct the $75 reward into an energy conservation mental category (like energy efficient lightbulbs), not energy expenditure, or else the reward would decrease the benefit of re-enrolling.

5.2 Fuzzy Regression Discontinuity Empirical Strategy

I use the discontinuity in the probability of continuing to a second challenge at the 9.5% conservation threshold for success, shown in Figure 2, as the instrument for treatment in a second conservation challenge. The instrumental variable is a binary indicator for success in the initial conservation challenge. The first stage relationship is:

$$C_i = \gamma_0 + \gamma_1 1\{R_i \leq \bar{R}\} + \gamma_2 R_i + \gamma_3 1\{R_i \leq \bar{R}\} \times R_i + \gamma_4 B_i + \gamma_{\mathbf{5}} \mathbf{X_i} + \eta_i \tag{3}$$

where C_i is a binary indicator for whether a household continues to a second challenge, R_i are households' credited changes in electricity use from the first challenge, $\bar{R}$ is the -9.5% threshold for success in the challenge, $1\{R_i \leq \bar{R}\}$ is the dummy variable for success in the initial challenge, B_i are the billed changes from the initial challenge, and $\mathbf{X_i}$ is a vector of other controls. B_i and $\mathbf{X_i}$ are not necessary for causal identification. In my main specification, I control for separate linear trends in credited reductions on either side of the discontinuity. The instrument excluded from the second stage is $1\{R_i \leq \bar{R}\}$.

The second-stage relationship is:

$$y_i = \beta_0 + \beta_1 C_i + \beta_2 R_i + \beta_3 1\{R_i \leq \bar{R}\} \times R_i + \beta_4 B_i + \beta_{\mathbf{5}} \mathbf{X_i} + \epsilon_i \tag{4}$$

where y_i is the post-challenge percent change in electricity use. y_i is defined:

$$y_i \equiv \frac{(u_{i,\tau=2} - u_{i,\tau=1})}{u_{i,\tau=0}} \tag{5}$$

where $u_{i,\tau}$ is household i's aggregate electricity use during the year indexed by event-time τ. For households that do not undertake a second challenge, $u_{i,\tau=2}$ is their total electricity use in the 12 months immediately following the completion of their initial challenge, $u_{i,\tau=1}$ is their total electricity use during their initial challenge, and $u_{i,\tau=0}$ is their use during the pre-program year. For households that immediately undertake a second conservation challenge with no gap between challenges, $u_{i,\tau=2}$ is the total electricity use during the second challenge and $u_{i,\tau=1}$ and $u_{i,\tau=0}$ are as before. For households that wait before beginning a second conservation challenge, I define $u_{i,\tau=2}$ as the 12 months of electricity use

during their second challenge and $u_{i,\tau=1}$ as the 12 months of electricity use immediately preceding that second challenge. This makes y_i a consistent measure of the reductions in electricity use a household is trying to achieve in its second challenge, regardless of whether that household waited before undertaking a challenge or began it immediately. I center the billed and credited changes at the 9.5% threshold. If (4) could be directly estimated without an instrument, β_0 would be the post-challenge change in billed electricity use at this threshold for households that do not continue in the program. β_1 is the additional effect on post-challenge billed changes in electricity use relative to households that left the program.

Causal fuzzy-RD estimates require households to be as good as randomly assigned at the discontinuity and the exclusion restriction to be satisfied. Due to the Team Power Smart design—in particular that the threshold for success was not known in advance to households and that there was a large ex-post weather adjustment—households were unable to precisely manipulate their assignment into treatment of success. This is supported by tests of the continuity of observables and a McCrary (2008) test of the density of observations, which fail to reject continuity at the 9.5% treatment threshold—details and a further discussion of identification are in Appendix E.

The exclusion restriction requires that success in the initial challenge only affects subsequent electricity use through the decision to re-enroll. This assumption could be violated if households respond to their success or failure in a way that directly affects their subsequent conservation effort, or if the $75 rebate causes an income effect and alters post-program conservation. As $75 is small relative to households' incomes, I assume there is no income effect that influences electricity use. Any emotional or behavior response to success and failure that directly affects subsequent conservation effort is likely to be particularly strong during the initial months of the next challenge while it is still fresh in a household's mind. By contrast, the event study estimates of Figure 1(b) indicate that additional energy conservation during the second challenge is consistent throughout the twelve months of the challenge, suggesting that there is no strong warm-glow or effect of disappointment on effort.

5.3 Fuzzy Regression Discontinuity Estimates

Across a wide variety of fuzzy regression discontinuity specifications and robustness checks, I find a consistent pattern in which re-enrolling in a second conservation challenge causes a large additional reduction in electricity use. These results are consistent with the event study results and support the finding that additional conservation challenges cause additional reductions in electricity use, and that electricity use partially rebounds as households leave the program. Table 3 presents my preferred specification. Columns (3) through (7) show results estimated for different bandwidths from ±7% to ±3% around the threshold of a -9.5% change in credited electricity use. Panel (A) shows the first-stage results for the probability of re-enrolling in a second challenge estimated from equation (3). For my preferred bandwidth of 5% I find that, conditional on failing the initial challenge, 53% of households at the 9.5% threshold re-enroll. Households that just succeed are 14.5 percentage points, or 27%, more likely to re-enroll than those which just failed. Across bandwidths from ±7% to ±3% I find the F-statistic on the instrument of success in the initial challenge decreases from 22 to 6.5. This indicates

that the first stage is reasonably strong for larger bandwidths, but the decreasing sample size limits the strength of the 1st stage as the bandwidth narrows.

Table 3 panel (B) reports the OLS, Reduced Form, and second-stage IV estimates of equation (4) for households who re-enroll within 12 months. Specification (1) is the OLS estimate; this shows that re-enrolling in a second challenge is associated with an on-average 1.6% decline in post-challenge electricity use relative to households that do not re-enroll. Specification (2) is the Reduced Form with a 5% bandwidth in Specification (5) and corresponds to the discontinuity in Figure 2(b). Specifications (3) through (7) show the IV estimates for different estimation bandwidths. These estimates are noisy yet find a consistent pattern in which, for households that comply with the instrument, continuing to a second conservation challenge causes a reduction in electricity use. Part of the explanation for the noisy estimates can be seen from Figure 2(b); the height of the reduced form discontinuity is sensitive to the trend functional form and bandwidth around the threshold. For my preferred bandwidth of 5% and a linear specification, I estimate that continuing to a second conservation challenge causes a 23% reduction in electricity use. This is a large effect.

In interpreting the IV estimates, it is important to account for these being local average treatment effects (LATE) for instrument compliers (Angrist and Pischke, 2008), and account for the definition of the outcome variable y_i being the post-challenge percent change in electricity use defined in Equation 5. y_i is the change in electricity use from a household's initial conservation challenge to the following year. 0% would mean a household maintains its initial challenge reductions (which were on average a 9.1% reduction compared to the pre-program year for a 5% bandwidth), a positive y_i is a rebound towards their pre-program use, and a negative y_i is an additional reduction in electricity use. The local IV estimate is for households achieving close to a 9.5% reduction in their initial challenge who comply with the instrument (success) by re-enrolling in a second challenge. This IV strategy cannot identify the level of electricity use for compliers who end their participation separately from compliers who re-enroll; it only identifies the difference—the treatment effect—caused by their re-enrollment. As a result, the 23% conservation caused by re-enrolling cannot be separated into the additional conservation (relative to the reduction achieved over the initial challenge) for those that re-enroll, and any rebound among those that do not re-enroll. With the OLS and event-study estimates being across all households—including compliers, always-takers, and never-takers—the relatively large IV estimate suggests that the average energy conservation is predominantly due to the instrument compliers, with the always-taker's and never-taker's contributing relatively little energy conservation as well as being unresponsive to their success or failure.

In Appendix G I undertake a variety of robustness checks. These include: 1st and 2nd order bias-corrected estimates and optimal bandwidths selected using the variance-bias trade-off method of Calonico, Cattaneo, and Titiunik (2014); a weak instruments test by Moreira (2003) that rejects (p-value 0.013, 5% bandwidth) the hypothesis that the binary indicator for Success (γ_1) is a weak instrument; a restriction of the sample to households experiencing small weather shocks; the use of additional covariates; the use of an alternate challenge gap length of 6 months; and an alternative specification using the log of monthly electricity use. While some estimates lose significance, especially

Table 3: **Fuzzy Regression Discontinuity Estimates of a Second Challenge**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A – First Stage				
Dependent variable: Continue to a Second Challenge C_i							
Window			±7 %	±6 %	±5 %	±4 %	±3 %
γ_1: Success Ind.			0.202***	0.190***	0.145***	0.137**	0.173**
			(0.0432)	(0.0468)	(0.0516)	(0.0573)	(0.0677)
γ_2: Cred. Reduc.			-0.532	-1.391	-2.937**	-1.290	2.090
			(0.778)	(0.971)	(1.244)	(1.760)	(2.765)
γ_3 : Success×			1.166	2.491*	2.565	-0.778	-3.973
Cred. Reduc.			(1.104)	(1.383)	(1.809)	(2.447)	(3.906)
γ_4 : Billed Reduc.			-0.300	-0.368	-0.0474	-0.282	-0.511
			(0.324)	(0.344)	(0.366)	(0.404)	(0.491)
γ_0 : Constant			0.487***	0.508***	0.530***	0.510***	0.475***
			(0.0303)	(0.0330)	(0.0364)	(0.0409)	(0.0479)
F-statistic			21.95	16.41	7.882	5.668	6.485
			Panel B – Second Stage				
Dependent variable: Percent change in post-challenge electricity use							
	OLS	RF	Instrumental Variable Estimates				
Window		±5 %	±7 %	±6 %	±5 %	±4 %	±3 %
β_1 : Re-Enroll	-0.0160***		-0.125**	-0.178**	-0.231**	-0.323**	-0.183*
	(0.00422)		(0.0605)	(0.0738)	(0.116)	(0.164)	(0.111)
β_2: Cred. Reduc.		-0.507*	-0.412*	-0.643*	-1.185*	-1.108	0.785
		(0.307)	(0.241)	(0.354)	(0.654)	(0.828)	(0.654)
β_3 : Success×		0.274	0.303	0.375	0.867	-0.229	-1.732
Cred. Reduc.		(0.442)	(0.310)	(0.426)	(0.624)	(0.985)	(1.229)
β_4 : Billed Reduc.		-0.0904	-0.0461	-0.113	-0.101	-0.216	-0.222
		(0.0986)	(0.0917)	(0.103)	(0.121)	(0.168)	(0.161)
Success Ind.		-0.0334**					
		(0.0132)					
β_0 : Constant	-0.00773***	0.0157*	0.0712**	0.103**	0.138**	0.184*	0.0944
	(0.00289)	(0.00912)	(0.0356)	(0.0447)	(0.0698)	(0.0950)	(0.0625)
N	5432	1475	2050	1763	1475	1196	888

Notes: Specification (1) is the OLS estimate across households. (2) is the Reduced Form corresponding to column (5). (3)-(7) are fuzzy-RD estimates corresponding to equations (3) and (4). Estimation sample for the OLS and IV is restricted to households that either start their next challenge within 12 months or do not undertake an additional challenge. The estimation window is restricted to ± the listed percent around the 9.5% threshold in credited changes. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

for small bandwidths, in all cases the point estimates maintain a consistent sign and large magnitude. This suggests that while the magnitude of point estimates varies, the causal effect of an additional conservation challenge is a large additional reduction in electricity use for those households whose decision to re-enroll in Team Power Smart is affected by their success or failure in their prior conservation challenge.

6 Conclusion

This paper investigates how households respond to repeated energy conservation goals. Using a ten-year panel of monthly electricity use, I study households' decisions to re-enroll in subsequent energy conservation challenges and estimate their long-run changes in electricity use. Those who succeed in achieving a goal typically differ from those who fail, and success typically results in different subsequent incentives. In contrast, the Team Power Smart program studied here randomized some households into success and failure, yet offered both successful and unsuccessful households the same information and same incentive to re-enroll. Using this natural experiment, I find that households' decisions to continue participating are notably discontinuous based on their success or failure, yet largely unresponsive to their degree of success. As a result, they do not make their re-enrollment decision consistent with being a conventional well-informed rational agent. Fuzzy regression discontinuity estimates find that re-enrolling causes large reductions in electricity use. I also use an event study model to estimate that electricity use continues to decline as households re-enroll in additional conservation challenges, but partially rebounds as households leave the program. The continued declines in electricity use as households participate, and rebounds if they do not, shows that the ongoing incentive of the goals and financial rewards are important for long-run lower electricity use.

That peoples' decisions to continue participating are highly responsive to a prior goal's success or failure is an important finding to consider in the design of many energy conservation and repeated goal programs. Voluntary programs are ubiquitous and by definition involve participation decisions. When participants do not respond solely to the marginal information and incentives provided, the impacts of past failure and success need to be accounted for. This makes the optimal goal-setting design dynamic; repeated goals should not be designed as repeats of single-attempt goals. For example, the continued reductions in electricity use as households continue to participate in Team Power Smart, and the rebound when they do not, demonstrates an important trade off: ambitious goals may incentivize effort within a goal, yet discourage continued participation if they lead to higher failure rates. Compared to a goal offered only once, the optimal goals of a repeated goal-setting program may be less ambitious once the impacts on subsequent participation are accounted for. Relatedly, programs may wish to avoid clear messages of failure in order to keep participation rates higher. Consolation prizes may be one way to raise participation rates by reframing failure to achieve an initial goal as success in achieving an intermediate goal.

This paper's demonstration of a stark discontinuous response to success and failure is a promising direction for research. Many programs beyond energy use provide consumers with detailed information

so they can make more informed decisions. If participation and effort decisions are made based on emotional reactions or simple heuristics like past success implies future success and past failure implies future failure, then how people interpret the information they're provided in the context of achieving a goal may be an important factor to consider alongside the content of the information itself. Even decisions that do not explicitly involve goals may invoke aspects of success and failure with corresponding discontinuous responses. For example, a household's repeated decisions of how much energy to use or how much to spend on entertainment can both involve periodic revealing of 'success' or 'failure' to stay within a budget. Programs beyond energy conservation which are focused on changing incentives or providing information may not alter decisions as expected if emotional and psychological mechanisms like disappointment aversion, the good news–bad news effect, or substantial inattention are widespread.

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