

The Behavioral Response to Voluntary Provision of an Environmental Public Good: Evidence from Residential Electricity Demand

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Abstract

This paper develops a theory of voluntary provision of a public good in which a household's decision to engage in a form of environmentally friendly behavior is based on the desire to offset another behavior that is environmentally harmful. The model generates predictions about (1) participation in a green-electricity program at the extensive and intensive margins, and (2) changes in electricity consumption in response to participation. We test the theory using billing data for participants and nonparticipants in a green-electricity program in Memphis, Tennessee. High-consumption households are more likely to participate, and they participate at higher levels. In terms of a behavioral response, households participating above the minimum threshold level do not change electricity consumption, but those participating at the minimum threshold increase electricity consumption 2.5 percent after enrolling in the program. The result is based on identification strategies that exploit before-after differences between participants and nonparticipants, and differences in the timing of enrollment among participants only. Despite the increase in electricity demand upon the purchase of green electricity for the households with a "buy-in" mentality, the net effect for the buy-in households is a reduction in pollution emissions, as the behavioral response is not large enough to offset the environmental benefit of the green-electricity purchase.

Keywords: green electricity; voluntary environmental protection; carbon offset; renewable energy; moral licensing, residential electricity demand

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1. Introduction

Why do individuals and households engage in pro-environmental behavior? It often comes at substantial private cost for frequently diffuse and, on its own, inconsequential public, environmental benefit. Such behavior is nevertheless common, especially in the realms of energy efficiency and the reduction of greenhouse-gas (GHG) emissions. Some behaviors, such as the purchase of a hybrid car, solar panels, or home weatherization products, can be justified on the basis of private payback periods, but the rate of return in many cases is too low to fully explain the prevalence of observed purchases. Other behaviors, such as the purchase of many green products, carbon offsets, and participation in green-electricity programs, operate more like charitable contributions.¹ With these behaviors, the primary goal is to promote environmental quality. This paper seeks to broaden the understanding of why we observe the latter type of pro-environmental behavior, referred to here as voluntary provision of an environmental public good.

We begin with a theory of voluntary provision in which a household's decision to engage in a form of environmentally friendly behavior is based on the desire to offset another behavior that is environmentally harmful. The interrelated behaviors that we consider throughout the paper are a household's conventional electricity consumption and participation in a voluntary green-electricity program that provides financing for electricity generation from renewable sources of energy. In this context, the theory is built on the idea—which we ultimately test—that households purchase green electricity in order to mitigate disutility associated with pollution emissions generated through their own consumption of conventional electricity. We consider two variants of the model's setup. In one version, a household cares about the exact amount of green-electricity it purchases. In the other version, a household only cares about whether it purchases the minimum amount required to participate in the green-electricity program. For both cases we derive conditions for participation at the extensive and intensive margins for a green-electricity program that is based on the voluntary contribution mechanism.

The model is also useful for examining how participation in the green-electricity program might affect demand for electricity more generally. Does participation in the green-electricity

¹ According to survey data, the number of consumers buying “green products” increased from 12 percent in 2007 to 36 percent in 2008, and remained at 36 percent in 2009 despite the recession (Mintel International Group, 2009). The voluntary carbon offset market grew over 15-fold between 2005 and 2008, increasing in size from \$45 million to \$705 million (Ecosystem Marketplace & New Carbon Finance, 2009). With respect to green electricity, over 5 million residential and commercial customers participate in such programs in order to provide financing for the generation of electricity through renewable sources of energy (REN21, 2009).

program affect a household's electricity demand? How might potential changes in electricity demand differ if participation is prompted with an offset motive or an offset motive combined with a "buy-in" mentality? And if electricity consumption changes, what is the net effect on emissions? It is easy to envision cases where households purchase a minimum amount of green electricity that is used to justify an increase in electricity demand; and if the increase in demand is greater than the purchase of green electricity, net emissions increase. With these questions in mind, we use the model to motivate the study of behavioral responses to voluntary provision of an environmental public good.

We then test implications of the model using billing data from the Green Power Switch (GPS) program in Memphis, Tennessee. We obtained data from Memphis, Light, Gas and Water (MLGW) on monthly electricity bills between 2003 and 2008 for all 910 households participating in the GPS program as well as a sample of 30,012 nonparticipating households.² In total, the dataset consists of more than 779,037 monthly observations. The GPS program at MLGW began in 2005, so we have billing data for two years before and three years after households could first participate in the program. The first part of our empirical analysis examines the relationship between average electricity consumption and decisions about participation in the GPS program. The models are based on cross-sectional variation in household electricity consumption prior to enrollment in the GPS program, and we evaluate the relationship between consumption and program participation at both the extensive and intensive margins. The second part of our analysis examines whether households that participate in the GPS program change their electricity consumption after doing so—that is, we test for a behavioral response to participation. We employ a fixed-effects research design whereby identification of the behavioral response is based on comparisons between participants and nonparticipants, before and after enrollment in the GPS program. We also estimate models that exploit before-after differences based on the timing of enrollment among participants only.

We find that households with greater electricity consumption are more likely to participate in the GPS program and to participate at a higher level. We interpret the results as consistent with our model—meaning that participating in the green-electricity program is motivated in part by households feeling an obligation to offset, to some degree, the pollution

² These data were provided in such a way that names and address were excluded from each observation to ensure anonymity of MLGW customers.

emissions associated with their own conventional-electricity consumption. With respect to evidence of a behavioral response, we find that when participants at all levels are lumped together, GPS participation does not lead to a statistically significant change in electricity consumption. If, however, we consider only participants that enroll at the minimum level, we do find evidence of a behavioral response: these households increase electricity consumption 2.5 percent after enrolling in the GPS program. This result, and the fact that it differs from that for participants at higher levels, is also consistent with our theoretical model, which links a “buy-in” mentality to expected differences in the behavioral response. Finally, given that in some cases the purchase of green electricity causes an increase in electricity consumption, we consider the net effect on emissions. It turns out that the 2.5 percent increase in consumption, which translates into 35 kWh/month for the average household, is less than the GPS minimum participation threshold of 150 kWh/month in green-electricity production. Hence, despite a behavioral response of increased electricity consumption, the net effect on environmental quality even for the buy-in households is a reduction in emissions.

The remainder of the paper is organized as follows. The next section reviews the most relevant literature and explains the contributions of our theoretical and empirical analysis. Section 3 develops the theoretical framework. Section 4 describes the GPS program and our data collection and preparation. Section 5 describes our empirical methods and reports the results. Section 6 summarizes and concludes.

2. Relation to Existing Literature

Economists often perceive pro-environmental behaviors, such as the voluntary purchase of green electricity, as examples of private provision of public goods. Important features of the standard model for privately provided public goods are developed in Bergstrom et al. (1986) and Andreoni (1988). The models are useful for understanding who provides public goods and who free rides. More recently, this approach has been extended to explicitly model consumption decisions within green markets (Kotchen 2006) and participation in green-electricity programs in particular (Kotchen and Moore 2007).

A substantial empirical literature examines the private provision of environmental public goods, and many studies focus on green electricity. Several studies employ stated- or revealed-preference techniques to derive estimates of willingness to pay for various types of green

electricity (e.g., Goett et al. 2000; Champ and Bishop 2001; Roe et al. 2001). Other studies analyze factors that influence participation in specific green-electricity programs (e.g., Oberholzer-Gee, 2001; Rose et al. 2002; Clark et al. 2003). In general, the results of this research show that households frequently state a willingness to pay a premium for green electricity, yet actual participation in programs depends on household characteristics, attitudes related to the environment, and the existence of “warm-glow” motives.³

The particular structure of a green-electricity program is another important factor that affects participation. Kotchen and Moore (2007) focus on the distinction between the two most common types of programs. The first are those based on the voluntary contribution mechanism (VCM). In VCM programs, households choose to contribute an additional amount of money each month, through their electricity bills, in support of green electricity, and the monthly contribution is fixed and independent of the household’s actual electricity demand. The second type of program is the green tariff mechanism (GTM). Households that participate in a GTM program pay a price premium for each unit of their actual electricity consumption, and the additional revenue is used to support green-electricity production. With the GTM, participation is more costly for households with greater electricity consumption, and Kotchen and Moore (2007) find that high-consumption households are less likely to participate in GTM green-electricity programs.

While understanding the determinants of participation in green electricity programs is important, it is also important to understand whether these programs lead to behavioral responses, such as an increase in energy consumption. In addition to our analysis in this paper, one other paper has examined whether enrolling in a green electricity program leads to changes in household energy consumption. Kotchen and Moore (2008) find that energy consumption fell for participants in a green-electricity program that was based on a GTM. The magnitude of the effect, however, was within the range obtained when multiplying the voluntary price premium by estimates within the literature on the price elasticity of demand for electricity. Hence the study could not determine whether the behavioral response was due to the voluntary price premium or some other response of households from having offset their emissions. In contrast, participants in

³ A “warm-glow” motive captures the idea that households might participate in a green-electricity program because it makes them feel good, rather than because they care about any public benefits that may arise from reduced pollution emissions. See Andreoni (1990) for the general formulation of warm-glow motives for private provision of public goods.

the green electricity program under study in the present paper contribute a fixed amount each month in support of green electricity through a VCM. Because this contribution does not change the marginal price of consuming electricity, any changes in consumption can be linked exclusively to a participating household's decision to offset some of its emissions.

The literature on green-electricity programs has relevance to the understanding of more recently formed markets for voluntary carbon offsets. Offsets are based on the idea that agents need not reduce their own emissions in order to reduce the amount of greenhouse gases (GHGs) in the atmosphere; instead, they can pay someone else to reduce emissions and achieve the same effect on atmospheric concentrations. Typically, offsets arise through investments in renewable energy, energy efficiency, reforestation, or other projects that reduce emissions or sequester GHGs. While the purchase of voluntary carbon offsets is consistent with private provision of a public good, it differs because provision is related to other behaviors that provide a public bad (Kotchen 2009). For example, climate change awareness campaigns, which emphasize how many consumer choices lead to increases in carbon emissions, have been shown to increase purchases of carbon offsets (Jacobsen 2011). Though the connection is rarely made (somewhat surprisingly), participation in a green-electricity program is very similar to voluntary purchases of carbon offsets. Households that are aware that their conventional electricity consumption generates GHG emissions may seek to offset those emissions through the purchase of green electricity.

It follows that many of the concerns about green electricity mirror those about carbon offsets. Households contribute a third or more of U.S. GHG emissions (Dietz et al. 2009), and carbon offsets may be an important component of policy efforts to reduce household GHG emissions (Vandenbergh and Steinemann 2007). But questions are frequently raised about whether the emission reductions are "additional" in the sense that they would not have occurred without the purchase of green electricity or offsets.⁴ Even if the emission reductions are additional, critics are still skeptical about the actual environmental benefits because of the potential behavioral response to such purchases. Many claim that carbon offsets are effectively indulgences that are used to assuage guilt and justify more polluting activities. In the context of green electricity, the same reasoning leads to questions about whether households that participate

⁴ See Conte and Kotchen (2010) for a discussion about additionality and how concerns about it affect the price of carbon offsets.

in programs consequently increase their consumption and thereby negate some (or all) of the supposed environmental benefits. More generally, the same type of behavioral response might exist across a broad spectrum of behaviors related to climate change or energy. Households that choose to weatherize their residence or purchase a more efficient heating and cooling system may be doing so, in part, to mitigate their own carbon emissions. Having done so, these households may become somewhat less concerned about curbing their emissions generated through other behaviors, and this behavioral response could potentially undercut the benefits of their initial action. In all cases, the explanation of the behavioral response is closely related to psychological theory on “moral licensing,” which is used to explain how individuals use their own “good” behaviors to self-justify “bad” behaviors.⁵ To date, however, we are not aware of any empirical evidence on the moral licensing of environmentally related behaviors that is based on measurable and revealed-preference data.

The present paper makes a contribution by linking participation in a green-electricity program with the offset motive. The theoretical model is novel and closely linked to an empirical application. Our results are consistent with the theory and differ in predictable ways from those of Kotchen and Moore (2007, 2008). A further contribution of the paper is that we provide revealed-preference evidence of a moral-licensing (or indulgence) effect with respect to environmentally related behavior. We find that the purchase of green electricity does in fact result in greater electricity demand for some households, but importantly, the behavioral response is not large enough to negate within household environmental benefits.⁶

3. Conceptual Framework

Households may choose to participate in a green-electricity program through a voluntary contribution mechanism. An important feature of the model that distinguishes it from previous work (i.e., Kotchen and Moore 2007) is that households choose to participate in order to

⁵ With experiments designed to test racial and gender prejudices, psychologists find strong evidence in support of moral licensing (Monin and Miller 2001). A more related psychology study, though not focused on green electricity and conducted using a laboratory experiment, finds that exposure to green products crowds out other types of altruistic behavior (Mazar and Zhong 2010).

⁶ The paper also contributes to the literature on heterogeneous behavior in charitable giving. Similar to our results, a recent study shows that individuals who donate small amounts to charities do so for different reasons than do those that give large amounts. In particular, DellaVigna et al. (2009) find evidence that individuals who give small amounts to charity are more likely to give their donations to avoid the disutility of saying “no” to a request than those who make larger donations.

minimize disutility from knowing their conventional electricity consumption generates emissions. We also consider the implications of a potential “buy-in” mentality that motivates participation.

A representative household with income m chooses between consumption of a numeraire x and electricity consumption y at price p_y . The household’s utility maximization problem is written as

$$(1) \quad \max_{x,y} \{x + f(y) - \gamma h(y) : x + p_y y = m\},$$

where $f(\cdot)$ is strictly increasing and strictly concave, $h(\cdot)$ is strictly increasing and convex, and $\gamma = \{0,1\}$ is an indicator variable for whether the household is concerned about its impact on environmental quality.⁷ The setup implies that while households of either type benefit from electricity consumption, only the type concerned with its own impact on environmental quality experiences disutility from knowing its conventional electricity consumption contributes to pollution emissions. The disutility may arise from knowledge about the impact of actual emissions or from subjective assessments about the impact of one’s own emissions. The first-order condition that defines the solution to (1), denoted \hat{y} , is

$$(2) \quad f'(\hat{y}) = p_y + \gamma h'(\hat{y}).$$

The solution for type $\gamma=1$ is illustrated in Figure 1 at the level of \hat{y} where the $f'(\cdot)$ and $h'(\cdot) + p_y$ curves intersect. Other elements of the figure are described below. We now consider the impact of introducing a green-electricity program, along with refinements on the motives for participation.

3.1 The Availability of Green Electricity

Consider a green-electricity program with participation structured around voluntary purchases of electricity g at price p_g , where g is measured in the same units as y (i.e., kilowatt-hours, kWhs). It is assumed that production of g does not generate emissions, and following Kotchen (2009), households of the type that are environmentally concerned care about the net effect on

⁷ The initial setup of our model is similar to that in Kotchen and Moore (2008); the only difference here is the further simplifying assumption that preferences are quasi-linear in x .

emissions. We can thus write the utility maximization problem with the green-electricity option as

$$(3) \quad \max_{x,y,g} \{x + f(y) - \mathcal{H}(y-g) : x + p_y y + p_g g = m\}.$$

Note that the purchase of green electricity is based on the amount of offsetting a household chooses to do, rather than on an all or nothing decision at 100 percent, which is the case under study in Kotchen and Moore (2008).

Assuming an interior solution for y , but allowing the possibility for $g = 0$, we have the following first-order (Kuhn-Tucker) conditions that define the solution to (3):

$$(4a) \quad f'(y) - p_y - \mathcal{H}'(y-g) = 0,$$

$$(4b) \quad g \geq 0 \text{ and } -p_g + \mathcal{H}'(y-g) \leq 0 \text{ and } g[-p_g + \mathcal{H}'(y-g)] = 0.$$

Letting $\{\tilde{y}, \tilde{g}\}$ denote the solution, we can make several useful observations. Condition (4b) implies that $\tilde{g} = 0$ if and only if $p_g > \mathcal{H}'(\hat{y})$. In words, if the price of green electricity exceeds the marginal disutility of emissions at the level of electricity demand without the offset option, then the household will choose not to offset any of its emissions. Clearly, this will always be the case for households of type $\gamma = 0$ or if the price of green electricity is sufficiently high; and in both cases it holds that $\tilde{y} = \hat{y}$. If $\tilde{g} > 0$, however, then it must hold that $\mathcal{H}'(\tilde{y} - \tilde{g}) = p_g$, which implies that if a household offsets at all, it does so all the way to the point where the marginal disutility from *net* emissions equals the marginal cost of offsetting, i.e., the price of green electricity. This condition is illustrated at the level \tilde{y} in Figure 1. Moreover, offsetting will be less than (equal to) 100 percent of electricity consumption if and only if $h'(0) < (\geq) p_g$.⁸ The case of less than 100 percent is illustrated with $\tilde{y} - \tilde{g} > 0$ in Figure 1. The alternative case (not shown) would require the intercept of $h'(0) + p_y$ to lie above $p_y + p_g$.

Let us for the moment add one feature to the model that is useful to motivate part of our empirical analysis. Among households of type $\gamma = 1$, assume the direct benefit of electricity consumption is $\alpha f(y)$, where $\alpha > 0$ is simply a weight that allows heterogeneity of electricity demand before green electricity is available. Using (2) it is easy to verify that $d\hat{y}/d\alpha > 0$; that is,

⁸ According to the model, households will never offset more than 100 percent of their emissions from electricity consumption. Such behavior would be possible, however, if the model were expanded to allow additional benefits to households of offset purchases, such as those often associated with warm-glow (Andreoni 1990) or status (Harbaugh 1998).

without the green-electricity option, demand for conventional electricity is increasing in α . From this, it follows that satisfying the nonparticipant condition of $p_g > \mathcal{H}'(\hat{y})$ is more difficult with a larger α . In other words, the model predicts that, among households concerned about environmental quality, those with greater observed conventional-electricity consumption are more likely to enroll in the green-electricity program. A further empirical prediction is that, assuming a household of type $\gamma=1$, higher consumption will be associated with the purchase more green electricity. This can be shown using (4a) and (4b) to verify that $d\tilde{y}/d\alpha = d\tilde{g}/d\alpha > 0$. For simplicity hereafter, however, we continue to analyze the model as if $\alpha=1$.

Further observations, which are important for our empirical analysis, are based on a comparison of electricity consumption before and after the green-electricity option is available, assuming a household participates. We have already shown that participation requires $p_g \leq \mathcal{H}'(\hat{y})$, where $\gamma=1$, and implies $p_g = \mathcal{H}'(\tilde{y} - \tilde{g})$. Substituting the latter condition into (4a) implies that conventional electricity consumption upon a household's participation must satisfy $f'(y) = p_y + p_g$, which corresponds with the quantity \tilde{y} in Figure 1. It is straightforward to verify using the figure that participating households will always (weakly) increase their conventional electricity consumption, that is, $\tilde{y} \geq \hat{y}$. It is also easy to verify using the figure that net consumption will always (weakly) decrease, that is, $\tilde{y} - \tilde{g} \leq \hat{y}$. Combining these results, we find that voluntary participation in the green-electricity program may be associated with an increase in electricity consumption, but the increase will be less than the amount of green electricity purchased.

3.2 *The Buy-In Mentality*

We now consider the possibility that when households choose to participate in the green-electricity program, they care not about their overall net emissions, but rather, about simply “buying in.” Our approach builds on Rose-Ackerman’s (1982) notion regarding motives for charitable giving. The idea is that if a “donor’s gift to a particular charity is at least equal to some minimum z , the donor believes that he or she has ‘bought in’ to the entire range of services provided by the charity” (p. 195). With respect to purchases of green electricity out of concern for the environment, the idea is that if some minimum amount of emissions is offset, a household

may feel it has done its part, and concern is no longer focused on actual net emissions. More formally, disutility from emissions no longer occurs conditional upon reaching the buy-in minimum.

We can modify the setup of our model to account for a buy-in mentality and to investigate its implications. Assume there is an exogenously given minimum threshold for the purchase of green electricity $g \geq z$. Based on this, the preference parameter γ now takes the form

$$(5) \quad \gamma(g; z) = \begin{cases} 1 & \text{if } g < z \\ 0 & \text{if } g \geq z. \end{cases}$$

That is, a concerned household cares about the environmental implications of its own electricity consumption unless it buys into the green-electricity program, in which case it no longer feels any “guilt.” In effect, there may still be the desire to offset, but only the minimum amount. With this modification, the household utility maximization problem becomes

$$(6) \quad \max_{x,y,g} x + f(y) - \gamma(g; z)h(y - g) : x + p_y y + p_g g = m, \quad g = 0 \text{ or } g \geq z.$$

Let us denote the solution(s) $\{\bar{y}, \bar{g}\}$. Clearly, the amount of green electricity purchased will take on only one of two values, $\bar{g} = 0$ or $\bar{g} = z$. One complete solution to the problem is thus $\{\hat{y}, 0\}$, which is simply the solution to problem (1) above. The other solution is $\{\bar{y}, z\}$, where \bar{y} solves $f'(y) = p_y$, as illustrated in Figure 1. Note that $\bar{y} > \hat{y}$, and it follows that conditional on buying-in to the program, households will always increase conventional electricity consumption. Moreover, the increase will be greater than that which would arise if participation were not motivated with a buy-in mentality.

To determine which of the two possible buy-in solutions will arise, consider indirect utility in both cases:

$$(7a) \quad V_{g=0} = m - p_y \hat{y} + f(\hat{y}) - h(\hat{y})$$

$$(7b) \quad V_{g=z} = m - p_y \bar{y} + f(\bar{y}) - p_g z$$

It follows that a household will buy-in to the offset program if and only if $V_{g=z} \geq V_{g=0}$, which can be rearranged to imply the following inequality:

$$(8) \quad [f(\bar{y}) - p_y \bar{y}] - [f(\hat{y}) - p_y \hat{y}] \geq p_g z - h(\hat{y}).$$

Because the left-hand side is strictly positive and $-h(\hat{y}) < 0$, there exists a threshold buy-in expenditure, denoted $\bar{\kappa} = p_g z$, that makes the household indifferent between the two possible solutions.⁹ Accordingly, if $p_g z$ is less than (greater than) $\bar{\kappa}$, the household will (will not) buy into the offset program. Note, here again, that if we consider direct benefits from electricity consumption to take the form $\alpha f(y)$, then satisfying (8) is only easier, implying that even among potential buy-in households, those with greater conventional-electricity consumption are more likely to participate.

Condition (8) is also useful to investigate the different possibilities for the change in net consumption—i.e., $\bar{y} - z$ versus \hat{y} —when participation is motivated with a buy-in. By definition, the net effect will be positive (neutral, negative) when $z > (=, <) \bar{y} - \hat{y}$, and it is easy to verify that all cases are possible. We can see that satisfying the inequality in (8) is possible for any value of z because p_g can vary without changes in \bar{y} or \hat{y} . Hence, even if the buy-in quantity is exceedingly high, participation is still possible if the price of green electricity is sufficiently low. In this case, the net effect can be positive. But, of course, if the buy-in quantity is very low, participation is also possible as long as the price of green electricity is not too high. It follows, in contrast to the previous version of the model where the net effect is always positive, that the net effect on electricity consumption—and therefore emissions—can be positive or negative when green electricity purchases are motivated with a buy-in mentality.

4 Empirical Setting and Data Collection

Memphis Light, Gas and Water (MLGW) is the largest three-service municipal utility company in the United States, serving more than 430,000 customers in Shelby County, Tennessee. MLGW purchases all of its electricity from the Tennessee Valley Authority (TVA), which has historically generated power using a mix of coal, natural gas, fuel oil, nuclear plants, and hydroelectric dams. Since April 2000, however, the TVA has added to its power mix electricity generated through solar power, wind power, and methane gas. TVA's development of these alternative energy sources is funded in part by the Green Power Switch (GPS) program, which is the voluntary green-electricity program under study in this paper.

⁹ In this knife-edged case, and only this case, the solution to maximization problem (6) is not unique.

The GPS program is a partnership between TVA and several electricity distributors, including MLGW, that allows customers to voluntarily increase the amount of electricity generated from solar energy, wind energy, and methane gas. Households that voluntarily enroll in the program agree to pay an additional amount on each month's energy bill. The exact amount added to the bill depends on how many blocks of green electricity a household chooses to purchase. Each block costs \$4 per month and covers the approximate cost of producing 150 kWhs of green electricity.¹⁰ Participating households must purchase at least one monthly block, but there is no limit to how many blocks a household can purchase. The vast majority of participating households purchase between one and five blocks, as we will show, and this translates into additional charges between \$48 and \$240 per year. Enrollment in the program does not change the type of electricity delivered to a household—the electricity consumed by GPS participants comes from the same fuel mix as that for non-participants—but money contributed to the GPS program provides funding for additional investment in green-electricity production.

MLGW initiated the GPS program in April 2005, and enrollment has increased steadily over time. Figure 2 shows the trends for new enrollment, cancelations, and active enrollment between the second quarter of 2005 and the fourth quarter of 2008. The initial pulse of enrollment was spurred in part by an advertising campaign accompanied with direct-mail reply cards and bill inserts when the program was first rolled out. Based on information provided by MLGW, we know that households responding to reply cards and bill inserts accounted for 141 of the 299 total enrollments in 2005. Beyond the initial advertising campaign, the GPS program has been promoted continually on the websites of both MLGW and TVA, and customers can enroll in the program directly through these websites. Web-based sign-ups are the most common way to enroll, accounting for 619 of the 885 households enrolled at the end of 2008. Other ways to sign-up include over the telephone, emails to MLGW staff, and enrollment at environmentally based community events and trade shows. Figure 2 shows a steady increase in enrollment and exceedingly few cancelations.

Our empirical analysis is based primarily on two sets of data that we obtained from MLGW. The first contains information about household participation in the GPS program,

¹⁰ This translates into a price of 2.67 cents/kWh for green electricity, and assuming a household chooses to purchase less green electricity than its conventional-electricity consumption, one could view participation in GPS program as a voluntary, green premium on infra-marginal units of electricity demand.

including when each household enrolled and how many blocks it purchased. If a household dropped out of the program or changed how many blocks it purchased, that information is also included, as well as the date any change occurred. The second dataset contains billing data on electricity consumption for all 910 households that ever participated in the GPS program and a sample of 30,012 non-participating households.¹¹ These data begin in May 2003, which is two years before the start of the GPS program, and continue through December 2008. For every observation, we have both a premise identification number and a customer identification number.¹² Hence, if a customer switches locations during the course of the sample, the billing record at the new location is treated as belonging to a new household. Similarly, if more than one customer occupies a premise during the sample period, we treat each customer's tenure as a separate household. It follows that the maximum number of monthly observations for a household is 68, but there are fewer observations for households that established service after May 2003 or that terminated service before December 2008.

We merge these two datasets together using each household's unique identification number. With the merged dataset, we then generate several variables that are central to our analysis. *Participant* is a time-constant dummy variable for whether a household ever enrolled in the GPS program, and *Blocks* is a time-constant variable for the number of blocks that a household purchased. If a household ever changed its level of participation, *Blocks* indicates the maximum ever purchased; and in the case of non-participating households, *Blocks* equals zero.¹³ *Enrolled* is a time-varying dummy variable indicating whether a household was actively enrolled in the GPS program in any given month (i.e., billing cycle). Finally, *kWh/day* is a time-varying variable for the amount of electricity consumed in each month, derived by dividing electricity consumption in each billing cycle by the number of days in the corresponding billing cycle.

¹¹ Ideally the sample of nonparticipating households would be truly random; however, MLGW programmers used the following procedure to draw the sample. Selected households are those with an address such that the second letter of the street name is "a" and the 4th digit of the address is "3", "5" or "9." Fortunately, for purposes of our analysis, the selection procedure does not appear to have any strong location biases. For example, the relationship between the population of a zip code and the number of households in our sample from that zip code has a strong positive correlation of 0.74. Throughout the paper we thus treat the sample as if it were randomly drawn.

¹² As mentioned previously, names and street addresses were excluded from all records to ensure the anonymity of MLGW's customers.

¹³ A total of 56 households changed their level of participation during the sample period. Nineteen households moved from one level of active participation to another, with 14 increasing blocks and 4 decreasing blocks. A total of 37 households dropped out of the program after having participated.

In addition to these MLGW data, all households were matched to zip-code level demographic data from the 2000 U.S. Census and election data from the 2000 presidential election.¹⁴ There are 35 different zip codes in the sample. Variables obtained from the Census include median household income, proportion with educational attainment of at least a college degree, share of households with families consisting of two people or more, population density (people per square kilometer), and race (proportion white and black). The electoral data include variables on the proportion of votes cast for George W. Bush, Albert Gore, and Ralph Nader in the 2000 U.S. Presidential Election.

The complete dataset includes 779,037 monthly observations; however, some observations were dropped in the process of cleaning and preparing the dataset for analysis. We drop the first billing observation on record for each household because the closing data of the previous billing cycle is not observed, meaning that we cannot calculate the number of days in the first billing cycle to generate *kWh/day* (31,102 observations, or 4.0 percent). We drop observations with a billing period shorter than 26 days or longer than 36 days, as these are considered irregular because meters are routinely read every 31 days (36,879 additional observations, or 4.7 percent). If the last observation for a household occurs before the end of our sample period, we drop this observation because electricity consumption may be abnormal during the month in which the account is cancelled (16,495 additional observations, or 2.1 percent). If the first observation for a household occurs after the start of our sample period, we drop the 2nd through 6th billing record because households typically experience a period of partial occupancy when first moving in (72,417 additional observations, or 9.3 percent). Finally, we drop all records for which electricity consumption is recorded as missing, negative, or zero (346, 8, and 3,922 observations, respectively, or collectively less than 1 percent). The final set of panel data used in our analysis includes 617,958 monthly observations and 20,205 households, 885 of which are participating households.

Table 1 reports summary statistics on the demographic and electoral data for the cross-section of 20,205 households. Note that these data are essentially zip-code level data weighted according to the number of households in our sample within each zip code. Median household

¹⁴ Precinct level data from the 2000 Tennessee Federal Election was downloaded from the Federal Elections Project (Lublin and Voss, 2001) and converted to zip-code level data using GIS software and Tennessee's zip code tabulation area (ZCTA) shape file and voting district shape file from the U.S. Census Cartographic Boundary Files. These shape files are available at <http://www.census.gov/geo/www/cob/>. To convert the data from precinct to zip code level data, each precinct was linked to the zip code where its centroid is located.

income is approximately \$45,400 per year, 27 percent of the adults within the zip codes have obtained at least a college degree, the proportion of white residents is 54 percent, roughly 69 percent of the households are families with two or more residents, and the mean population density is 906 persons per square kilometer. In terms of electoral preferences in the 2000 presidential election, 42 percent voted for Bush, 56 percent voted for Gore, and just over 1 percent voted for Nader. The final row of Table 1 includes summary statistics for mean *kWh/day*, which is based on MLGW monthly billing data averaged within households and then between households. We find that mean electricity consumption is approximately 40 kWh/day, or 1,200 kWh/month.

Comparing across participants and nonparticipants, we find that participating households use more electricity and tend to be located in zip codes with higher median incomes, more college graduates, more whites, fewer families, and greater population densities. There does not, however, appear to be meaningful differences between participants that purchase one block or more than one block, with the exception that the latter group has higher electricity consumption. In the next section, we examine the influence of these variables on the extensive and intensive margins of participation more rigorously using a regression framework.

Table 2 reports the frequency distribution of the GPS participation levels (i.e., *Blocks*) among the 910 households that ever participated in the program. Nearly half (45 percent) of all households purchase only one block, and it is worth mentioning that this fact is itself consistent with the existence of a buy-in effect. Not surprisingly, as the number of blocks increases, there tends to be fewer households participating. One clear exception, however, is the spike at 5, which is likely due to the layout of the website sign-up form that solicits levels of enrollment up to five blocks, beyond which households must enter an “other” category and fill in their desired level. Overall, the average level of participation among participants is 2.3 blocks at a cost of \$9.20 per month, or \$110.40 per year.

5 Empirical Analysis

We now turn to the empirical analysis with a focus on three primary questions: What explains the extensive and intensive margins of participation in the Green Power Switch (GPS) program? How does a household’s participation affect its conventional-electricity consumption? And what is the net effect on environmental quality?

5.1 The Participation Decision

The conceptual framework developed in Section 2 is built around that idea that households may choose to participate in the GPS program in order to offset emissions from their conventional electricity consumption. If the offset motivation does in fact exist, it is reasonable to expect, *ceteris paribus*, that households with greater electricity consumption are more likely to participate in the GPS program, and to a greater extent. To evaluate whether this pattern holds in the data, we begin with estimation of a cross-sectional probit model in which we regress the dummy variable for each household's participation decision, *Participant*, on its average electricity consumption along with the corresponding demographic and electoral data at the zip-code level. For this model, and all other cross-sectional models, we use *kWh/day* as an explanatory variable that is averaged over only those months when households are not participants in the GPS program. This avoids the potential endogeneity, which we investigate later, of electricity consumption changing due to having participated in the GPS program.¹⁵ For all cross-sectional models we cluster standard errors at the zip-code level to account for potential spatial correlation of the errors and also for the unit upon which the demographic and electoral variables vary.

Columns (1) and (2) of Table 3 report the estimated marginal effects of two probit models. In the first we include *kWh/day* (divided by 10 to ease interpretation), and in the second we include an additional quadratic term for *kWh/day* to allow a more flexible functional form. We find significant differences between participants and nonparticipants in the sample, though the magnitudes are small.¹⁶ Based on the model in column (1), we find that an increase of 10

¹⁵ Though the results are not reported here, we also carryout the cross-sectional analysis using two alternative constructions of average electricity consumption. Our procedure of using only electricity consumption in months prior to participation implies that 84 participant observations are not included in the models because they do not have at least six months of data prior to having participated in the GPS program. If, however, we simply take average electricity consumption using all months, and therefore include these 84 additional observations, the results are very similar to those reported in Table 3. Another alternative that we try is to use a detrended *kwh/day* that accounts for potential bias due to having different months over which averages are taken for participants and nonparticipants. But again, the results are very similar to those reported in Table 3.

¹⁶ We report and discuss unweighted results throughout the paper; however, we recognize that our sample is choice-based. This occurs because of the different sampling probabilities of participating households ($Pr = 1$) and nonparticipating households ($Pr = 0.05$). If one were interested in population level marginal effects, the models should be weighted to correct for the disproportionate sampling, but our primary interest here is on testing for differences among households within the sample, for which the unweighted models are appropriate. We nevertheless estimated weighted models and the primary difference is that the weighted estimation produces coefficients that are substantially smaller in models where the left-hand side variable includes participants and nonparticipants. There are

kWh/day on average increases the probability that a household in the sample is a participant in the GPS program by 0.23 percentage points. This result, which occurs after controlling for the demographic and electoral variables at the zip-code level, is consistent with a simple comparison of means: *kWh/day* is significantly greater for participants than nonparticipants (49.6 *versus* 39.6, $t = 10.52$, $p < 0.01$). According to the model in column (2) the quadratic term is statistically significant, and allowing this more flexible functional form increases the magnitude of the estimate such that an increase of 10 kWh/day increases the probability that a household is a participant by 0.36 percentage points. Among the zip-code level variables, only the share of votes for Ralph Nader is statistically significant. While the magnitude is small, households from zip codes with a greater share of votes for Nader are more likely to be participants in the GPS program.¹⁷

Turning now to the intensive margin of participation, we estimate a truncated regression model in which the level of participation, *Blocks*, is regressed on the same covariates.¹⁸ We find that greater conventional electricity consumption is associated, in a statistically significant way, with the purchase of more blocks in the GPS program. According to the linear specification in column (3), an increase of 10 kWh/day increases the number of blocks of green electricity that participants purchase by 0.05. The non-linear specification in column (4), however, suggests that the marginal effect of *kWh/day* on the number of blocks purchased is increasing and concave. One may interpret this result as evidence that the positive marginal propensity to offset emissions diminishes with higher levels of electricity consumption. Among the zip-code level variables, a notable result is that for median household income, we find some evidence that income is negatively associated with the number of offsets purchased. Though it would be better to have data on income at the household level, this result even with zip-code level data is important because it provides evidence against the alternative explanation that both conventional electricity consumption and GPS blocks are normal goods, which could possibly explain the positive correlation. Instead, we have attempted to control for income and, if anything, find that it is

no differences in terms of which coefficients are statistically significant. Coefficients in columns 3 and 4 of Table 3 are unaffected by weighting because the sample is limited to participants only. All coefficients reported in Tables 4 and 5, which present the fixed effects estimates discussed later in the paper, are identical or extremely similar in both the weighted and unweighted models.

¹⁷ Though not reported, we also estimate models excluding the zip-code level covariates, and in all cases, the coefficients of interest on *kWh/day* are very similar to those reported in Table 3.

¹⁸ The truncated regression models are based on the sample of all participating households, with the exception of those households that did not have a billing cycle on record prior to their enrollment in the GPS program.

negatively associated with the number of GPS blocks purchased. Hence the pattern of results supports the notion that the intensive margin of GPS participation is motivated, at least in part, by the desire for households to offset their own emission from electricity consumption.

The other results in Table 3 are for models that combine the extensive and intensive margins into one estimator. The Tobit models in columns (5) and (6) essentially combine the probit and truncated models into one (Greene 2002), and not surprisingly, the qualitative results are very similar. Most importantly, *kWh/day* continues to have a positive and statistically significant effect on participation when both the extensive and intensive margins are considered simultaneously. Finally, we estimate the negative binomial models in columns (7) and (8) primarily as a robustness check. Count data models are useful for our application because of the preponderance of zeros, along with the high number of counts at a low numbers of blocks, which then taper off relatively quickly. Even with the different functional form assumption of the negative binomial model, we again find that participation in the GPS program increases, but at a decreasing rate, with a household's level of conventional electricity consumption. Moreover, household income, at least when measured at the zip-code level, does not have a statistically significant effect, but the vote share going to the Green Party's Ralph Nader does have a positive and statistically significant effect on participation, which is consistent with results of the previous models.

5.2 *The Behavioral Response to Participation*

We now consider the question of whether or not participation in the GPS program affects household electricity consumption. A prediction of the conceptual framework developed in Section 3 is that conditional on participation in the GPS program, a household will (weakly) increase its electricity consumption. Moreover, if participation is motivated with a buy-in mentality, the model predicts that the increase in electricity consumption will be even greater.

We begin testing the effect of GPS participation on electricity consumption using fixed-effects models that compare changes in the electricity consumption of participants before and after GPS enrollment to changes in the electricity consumption of nonparticipants over the same period. Our basic specification is

$$(9) \quad \ln(kWh/day)_i = \beta Enroll_{eq} + \delta M_{i,t} + v_i + \varepsilon_i$$

where, as defined previously, kWh/day_{it} is average daily electricity consumption for household i in billing cycle t ; $Enrolled_{it}$ is a time-varying dummy variable indicating whether household i is participating in the GPS program in billing cycle t ; M_{it} is a vector of month-year variables throughout the sample period for the share of days in household i 's billing cycle t that falls in each month (sixty-seven in total);¹⁹ v_i is a household-specific intercept; and ε_{it} is a normally distributed error term. In all estimates, we cluster standard errors at the household level, which makes statistical inference robust to potential serial correlation of residential electricity consumption.

The coefficient of primary interest is β , as it provides an estimate, based on a comparison between participating and nonparticipating households, of how electricity consumption changes upon participation in the GPS program. While specification (9) estimates the average effect of all participants regardless of the number of blocks that a household purchases, we later relax this assumption when testing for evidence of the buy-in effect. It is important to recognize that the empirical model controls for all time-invariant differences between households, but it does not control for time-varying differences. Hence the key identification assumption in our baseline empirical strategy is that, in the absence of GPS participation, the trend in electricity consumption would have been the same in both participating and nonparticipating households. This is the “common trends” assumption that is required in both fixed-effects and difference-in-differences research designs (Meyer, 1995).

While the common trends assumption cannot be tested formally, we can examine the existence and direction of potential bias using different subsets of the data. To address the potential concern that participating and nonparticipating households may have different trends in electricity consumption, we estimate a model identical to specification (9) that includes only participating households. This model takes advantage of a different identification strategy based on variation in the timing of participation among participating households only.

Another potential source of bias, however, is that the timing of GPS enrollment is endogenous. Suppose, for example, that a household experiences a change in personal ideology

¹⁹ Note that if billing cycles aligned perfectly with calendar months, the month-year variables would be simply month-year fixed effects. The advantage of our approach is that we more accurately attribute electricity consumption to the time periods in which common shocks actually took place. We did, however, estimate models in which we simply use month-year fixed effects based on the end of a household's billing cycle and the magnitude of coefficient estimates are nearly identical and the levels of statistical significance are unchanged.

and decides to take personal steps to conserve energy. The household might simultaneously decide to enroll in the GPS program while also making behavioral changes at home to reduce energy consumption. Under such a scenario, the endogeneity would cause negative bias in the estimate of β . To address this possibility, we estimate another version of specification (9) that includes all nonparticipating households and only participating households that joined the GPS program in 2005, the year the program first began. These households comprise 35 percent of the participating households. For such initial joiners of the GPS program, it is reasonable to assume that participation was caused by the (exogenous) introduction of the program rather than a simultaneous change in personal ideology.

Table 4 reports the estimates of β in specification (9) for all three identification strategies: full sample, participants only, and initial joiners with nonparticipants. The point estimate in the full sample model of 0.003 implies that enrollment in the GPS program leads to 0.03-percent increase in household electricity consumption, but not only is the effect small, it is also not different from zero with any meaningful degree of statistical significance. Despite the entirely different estimation strategy of the participant only model, the coefficient is very similar at 0.006 and also not statistically distinguishable from zero. Finally, when considering only the initial joiners and nonparticipants the coefficient increases to 0.008 but is still not statistically significant. Together, these models provide no evidence that household electricity consumption changes upon participation in the GPS program, at least when participation at all levels of the intensive margin are considered jointly.

We now test for evidence of the buy-in effect by relaxing the assumption that the behavioral response to participation in the GPS program is uniform across all levels of the intensive margin. Specifically, we test for differential responses between households that purchase one block (i.e., the minimum level) and those that purchase more than one block. Our approach is to simply expand the empirical specification to

$$(10) \quad \ln(kWh/day_{it}) = \beta_1 Enrolled[1]_{it} + \beta_2 Enrolled[>1]_{it} + \delta \mathbf{M}_{it} + v_i + \varepsilon_{it}$$

where the only difference is that we estimate separate β s for participating households that purchase one block and households that purchase more than one block. In effect, we estimate different behavioral responses for those participating in a way consistent with the buy-in effect

and those that are not. Again, we estimate specification (10) with a fixed-effects model, cluster standard errors at the household level, and employ all three of the identification strategies.²⁰

Table 5 reports the three different estimates of β_1 and β_2 , and we find differences between them. Consistent with the theoretical model, we find that, on average, households participating in the GPS program at the minimum level increase their electricity consumption after participating. The magnitude is such that they increase consumption by approximately 2.5 percent, and the result in all three models is statistically significant (at the 90-percent level with a two-tailed test, or the 95-percent level with a one-tailed test). In contrast, we find no evidence that households purchasing more than one block change their electricity consumption, which is consistent with our previous results. In fact, the point estimate in all three models, though not statistically different from zero, is negative. Additionally, tests of whether $\hat{\beta}_1 = \hat{\beta}_2$ are rejected in all three cases with p -values of .037, .054, and .086 for columns (1), (2), and (3), respectively. Hence we interpret these results as providing evidence of the buy-in effect for participation in the GPS program. Not only do those purchasing the minimum amount of green electricity increase their electricity consumption; their behavioral response differs from other participating households that purchase more than one block. What is more, a striking feature of the results is how robust the estimates are across the three distinct identification strategies. In particular, the control group for comparison is different in columns (1) and (2) of Table 5, yet the results remain very similar.²¹

5.3 Net Consumption and Environmental Quality

Households voluntarily purchase green electricity as a more environmentally friendly alternative to conventional electricity. But if participation in a green-electricity program prompts an increase in electricity demand, then the impact on generation of conventional electricity, and therefore environmental quality, depends on the net effect of the offset purchases versus any change in demand.

²⁰ We also estimated models in which we test for differences between other levels of participation, but we do not report the results because we found no statistically significant differences.

²¹ We also estimated models to explore the potential existence of trends in the behavioral response to participation. Specifically, we estimated models with a different “treatment” effect for each month after participation for the first year. We do, however, lose statistical power when estimating these coefficients because the number of observations for each is substantially lower. For the one-block households, the point estimates indicate that the response is perhaps largest in the first few months after enrollment, but this evidence is quite weak, as nearly all monthly coefficients are not statistically different from each other.

Let us first consider participating households that purchase more than one block. For these households, we find no significant change in electricity demand. Among them, the average level of participation is 3.4 blocks, which translates into a green-electricity production of 510 kWh/month, or 6,120 kWh/year. To get a sense for the environmental impact, we use the U.S. Environmental Protection Agency's published emission rates for the Tennessee Valley Authority (eGrid 2010). Focusing on the three primary pollutants of sulfur dioxide, nitrous oxide, and carbon dioxide, we find that the average (non-buy-in) household offsets 6,120 kWh/year of conventional electricity with emission-free green-electricity, and thereby reduces their own annual emissions by 8,129 lbs of CO₂, 35 lbs of SO₂, and 15 lbs of NO_x. This translates into a 43-percent reduction in a household's electricity-related emissions. Although net CO₂ emissions are reduced, the actual changes in aggregate emissions of SO₂ and summertime NO_x are less clear because the emissions by Tennessee power producers are capped under the Acid Rain Program and the NO_x Budget Program; and trading when these caps are binding implies that emission reductions in one location may be offset with increases in another.

Now consider the set of households that purchase only one block of green electricity. We find that these households increase electricity consumption 2.5 percent on average after participation. Based on the average monthly consumption of 1,418 kWh/month among households purchasing one block, this 2.5 percent increase in electricity demand translates into a 35 kWh/month increase in consumption. This quantity is easily exceeded by the 150 kWh/month increase in the production of green-electricity. In effect, with the buy-in effect, 23 percent of the green-electricity emission reductions are offset by increased electricity consumption. Overall, for these households, the average net reduction of their own annual emissions is 1,913 lbs of CO₂, 8 lbs of SO₂, and 3 lbs of NO_x. This translates into a 10-percent reduction in a household's electricity-related emissions, but again, understanding the aggregate change emissions for different pollutants requires consideration of whether cap and trade policies are binding at any given time.

6 Summary and Conclusion

This paper investigates why households engage in pro-environmental behavior and whether such behaviors are in fact beneficial for the environment. We develop a theory of voluntary provision of an environmental public good that is motivated by the desire to offset other behavior that is

environmentally harmful. We apply the theory to a setting in which households may purchase green electricity in order to mitigate disutility associated with pollution emissions generated through their own consumption of conventional electricity. We consider cases in which a household purchases green electricity because it cares about its actual level of emissions or because it simply wants to buy-in to the program. In both cases, the model predicts that, *ceteris paribus*, households with higher electricity consumption are more likely to purchase green electricity. Moreover, in the case where households care about the actual level of emissions, the model predicts that high-consumption households are likely to purchase more green electricity. The model also generates testable predictions about the expected behavioral response to participation in the green-electricity program. Because the purchase of green electricity affords participating households a cost effective way to offset concerns about their own emissions, the model predicts that participating households will increase their electricity consumption; the increase is also expected to be larger for households that simply buy-in to the program.

We find that households with greater electricity consumption are in fact more likely to participate in the green-electricity program and to participate at a higher level. Regarding the behavioral response, we find that when participating households at all levels are considered together, there is no statistically significant change in electricity consumption after participation. If, however, we consider separately the participating households that enroll at the minimum level—i.e., households that are most likely exhibiting a buy-in mentality—then we do find a statistically significant behavioral response. These households increase electricity consumption 2.5 percent after enrolling in the green-electricity program. Notably, this result is robust to identification strategies based on before-after differences between participants and nonparticipants, and between the timing of enrollment among participants only.

The fact that electricity consumption increases for some households that purchase green electricity raises the question of whether the net effect on emissions is positive or negative for the environment. We find that the behavioral response of increased electricity consumption remains less than the minimum production of green electricity that a household must purchase. Hence the net effect is a reduction in pollution emissions. This may not always be the case, however, and our results underscore the importance of taking the behavioral response into account when designing and evaluating the effectiveness of green-electricity programs. Fortunately existing green-electricity certification programs appear to recognize this need and

address it with minimum purchase requirements. The Green-E national standards for certification in the United States, for example, requires that production based green-electricity programs selling block products, as in the program that we study here, must require a minimum block purchase of 100 kWh/month. Our results suggest that this minimum purchase is large enough to ensure that the behavioral response is not sufficiently large that green-electricity programs become a counterproductive means for reducing emissions. It is unclear, however, whether a different minimum allowable purchase might have achieved a greater overall emission reduction, which a question that we leave for future research.

While the theoretical and empirical results of this study have clear implications for the evaluation of green-electricity programs, they also contribute to the understanding of green consumer behavior more generally. The supposed environmental benefits of green goods and services are often questioned for reasons beyond the credibility of marketing claims. As discussed previously, arguments are frequently made that the availability of green options, and the numerous government programs that subsidize their consumption, are problematic from an environmental standpoint because they may simply promote greater consumption. The arguments are perhaps most salient in the context of carbon offsets where critics emphasize concerns about moral licensing, whereby carbon offsets are indulgences used to justify even greater emissions. The problem with these claims, however, is that empirical evidence based on observable and quantifiable behavior is generally missing. Our results thus contribute to the debate, as we find real evidence for a behavioral response consistent with greater consumption—but it is not large enough to reverse the intended environmental benefits.

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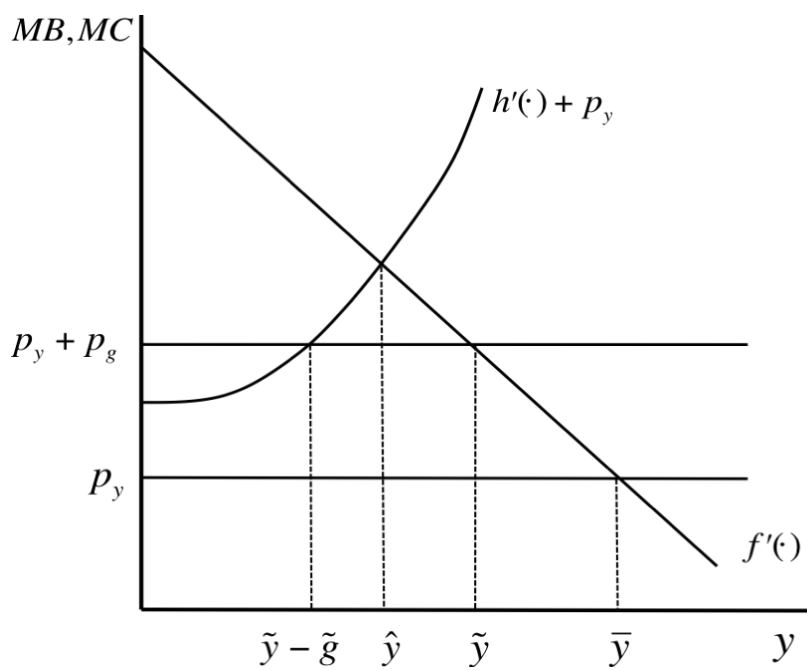


Figure 1: Relative electricity consumption for type $\gamma=1$ with and without the green electricity program

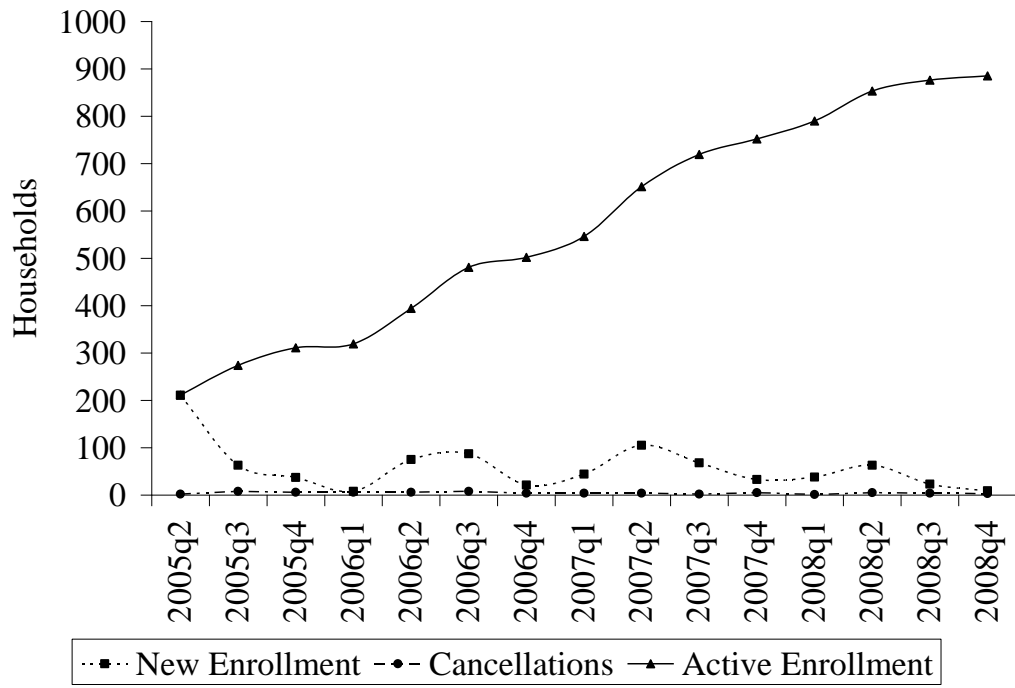


Figure 2: New enrollment, cancellations, and active enrollment in MLGW's Green Power Switch program

Table 1: Summary statistics pooled and by nonparticipants and participants

	Full Sample	Non-Participants	Participants (Blocks = 1)	Participants (Blocks > 1)
Median income (\$1,000s)	45.377 (18.529)	45.169 (18.311)	50.52 (22.210)	49.461 (22.408)
Bachelor's degree (1=yes)	0.27 (0.155)	0.266 (0.154)	0.372 (0.143)	0.367 (0.144)
Race white (1=yes)	0.544 (0.308)	0.537 (0.309)	0.697 (0.250)	0.692 (0.239)
Family household (1=yes)	0.686 (0.112)	0.689 (0.107)	0.628 (0.169)	0.623 (0.165)
Population density (#/km ²)	905.636 (524.727)	899.601 (520.825)	1000.803 (596.468)	1065.427 (581.814)
Vote Bush (1=yes)	0.421 (0.241)	0.418 (0.241)	0.497 (0.214)	0.491 (0.210)
Vote Gore (1=yes)	0.564 (0.243)	0.567 (0.244)	0.481 (0.210)	0.486 (0.206)
Vote Nader (1=yes)	0.011 (0.007)	0.011 (0.007)	0.018 (0.010)	0.018 (0.010)
kWh/day	40.023 (26.508)	39.61 (25.806)	45.904 (32.633)	51.43 (41.025)
Observations	20,205	19,320	384	501

Notes: Standard deviations are reported in parentheses. Summary statistics are based on 20,205 households. Demographic data are from the 2000 U.S. Census. Electoral data are from the Federal Elections Project. Electricity consumption data are from Memphis Light, Gas, & Water. Of the 910 households that participated in the GPS program, 25 are excluded from the sample for reasons describes in Section 4 of the main text.

Table 2: Frequency of Green Power Switch enrollment levels

# of Blocks	# of Households	Annual Contribution (per household)	Proportion of participants
1	395	\$48	0.45
2	263	\$96	0.30
3	81	\$144	0.09
4	40	\$192	0.05
5	101	\$240	0.11
6	5	\$288	0.01
7	2	\$336	0.00
8	7	\$384	0.01
9	1	\$432	0.00
10	8	\$480	0.01
11	1	\$528	0.00
12	2	\$576	0.00
15	2	\$720	0.00
20	1	\$960	0.00
30	1	\$1,440	0.00

Average # of Blocks: 2.3 (\$9.20/month or \$110.40/year)

Notes: This table displays how many households have ever enrolled at each number of blocks. There is a total of 910 households. For 24 households that changed their enrollment levels, this table reports the household's greatest level of enrollment.

Table 3: Marginal effects from cross-sectional models of the extensive and intensive margins of Green Power Switch participation

	Probit		Truncated		Tobit		Negative binomial	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KWh/day	0.0023*** (0.0007)	0.0038*** (0.0011)	0.0533*** (0.0173)	0.1774*** (0.0512)	0.0058*** (0.0018)	0.0100*** (0.0028)	0.1423*** (0.0270)	0.2010*** (0.0341)
(kWh/day) ²	--	-0.0001** (0.0000)	--	-0.0039*** (0.0013)	--	-0.0002** (0.0001)	--	-0.0038*** (0.0008)
Median income (\$1,000s)	0.0001 (0.0006)	0.0001 (0.0006)	-0.0048 (0.0061)	-0.0093* (0.0056)	0.0001 (0.0014)	0.0000 (0.0014)	-0.0047 (0.0221)	-0.0052 (0.0222)
Bachelor's degree (1=yes)	0.0661 (0.0596)	0.0687 (0.0591)	0.3148 (1.0114)	0.3823 (0.9902)	0.1603 (0.1365)	0.1670 (0.1348)	2.2759 (2.1130)	2.2880 (2.1162)
Vote Gore (1=yes)	0.0557 (0.0824)	0.0578 (0.0809)	-1.0117 (1.1629)	-0.4217 (1.1325)	0.1090 (0.1896)	0.1147 (0.1849)	0.0863 (3.0131)	0.2410 (3.0335)
Vote Nader (1=yes)	2.3504*** (0.7047)	2.3279*** (0.7033)	-1.7788 (11.6345)	-5.4937 (11.4648)	5.3862*** (1.6453)	5.2956*** (1.6332)	87.7194*** (30.2631)	87.2393*** (30.5049)
Population density (#/km ²)	0.0000 (0.0000)	0.0000 (0.0000)	0.0003 (0.0002)	0.0003* (0.0002)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0003)	0.0000 (0.0003)
Race white (1=yes)	0.0415 (0.0660)	0.0429 (0.0648)	-0.8681 (0.8141)	-0.2735 (0.8395)	0.0836 (0.1523)	0.0876 (0.1486)	0.5215 (2.4394)	0.6434 (2.4589)
Family household (1=yes)	-0.0046 (0.0625)	-0.0035 (0.0621)	0.0627 (0.7368)	0.3754 (0.6772)	-0.0036 (0.1414)	0.0005 (0.1399)	-0.0878 (2.0994)	-0.0748 (2.1102)
Observations	20,121	20,121	801	801	20,121	20,121	20,121	20,121
Log likelihood	-3018.50	-3013.49	-1469.46	-1461.95	-4500.28	4493.18	-4422.80	-4418.55

Notes: All coefficients are marginal effects, which are reported at the means for the nonlinear models. KWh/day is divided by ten in all regressions to ease interpretation of the coefficients. Eighty-four participating households that do not have valid consumption data on record prior to enrolling in the GPS program are excluded from these models. Standard errors clustered at the zip-code level are reported in parentheses. One, two, and three asterisk(s) indicate significance at the 90-, 95-, and 99-percent levels, respectively.

Table 4: Fixed-effects models of the effect of Green Power Switch participation on household electricity consumption

	(1)	(2)	(3)
	Full Sample	Participants only	Initial joiners and nonparticipants
Enrolled in GPS	0.003 (0.009)	0.006 (0.009)	0.008 (0.011)
Observations	617,958	42,646	592,563
<i>R</i> -squared	0.387	0.539	0.381

Notes: Dependent variable is $\ln(kWh/day)$. Household fixed effects are included in all regressions along with month-year variables for each billing cycle. Standard errors clustered at the household level are reported in parentheses. One, two, and three asterisk(s) indicate significance at the 90-, 95-, and 99-percent levels, respectively.

Table 5: Fixed-effects models of the effect of Green Power Switch participation at different levels on household electricity consumption

	(1)	(2)	(3)
	Full Sample	Participants only	Initial joiners and nonparticipants
One block	0.023* (0.013)	0.025* (0.013)	0.027* (0.015)
More than 1 block	-0.012 (0.011)	-0.007 (0.012)	-0.010 (0.016)
Observations	617,958	42,646	592,563
<i>R</i> -squared	0.387	0.539	0.381

Notes: Dependent variable is $\ln(kWh/day)$. Household fixed effects are included in all regressions along with month-year variables for each billing cycle. Standard errors clustered at the household level are reported in parentheses. One, two, and three asterisk(s) indicate significance at the 90-, 95-, and 99-percent levels, respectively.