Green is Good—The Impact of Information Nudges on the Selection of Voluntary Green-Power Plans

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ABSTRACT

A recent trend has been a move toward greater reliance on renewable or "green" energy sources, especially in the residential sector. Using a choice experiment, this paper examines how providing information regarding the efficiency, cost, and environmental impacts of different power-generating sources impact consumers' stated preferences for selecting voluntary green-power plans. Based on 21,000 plan choices from two different samples totaling over 1,800 respondents, our results indicate that information nudges significantly impact respondents' choice of plan. Promoting the advantages of the green plan *or* the disadvantages of the "gray" plan increase green plan selection. The magnitudes of these estimated effects are economically significant being roughly equivalent to a change in the monthly green price premium of $4/month. We also find that promoting the advantages of the green plan is more effective when the green plan premium is relatively small, while highlighting the drawbacks of the gray plan is more effective when the green plan premium is relatively large. Our results suggest that information nudges have the potential to be a plausible, economical, and effective mechanism to increase adoption of voluntary green-power plans.

Keywords: Renewable energy, Green power, Information, Nudge, Choice experiment

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1. INTRODUCTION

In the U.S., as well as in many other developed nations, there has been a growing trend toward greater reliance on renewable energy. One prominent area embodying this increase in renewables is electric power generation, both in the U.S. and globally. As of 2018, the U.S. Energy Information Administration (EIA) reported that approximately 56% of renewable energy is used for electric power generation, and electric power generated from renewable sources accounted for roughly 17% of the total generation in the U.S.[1] Furthermore, the U.S. Department of Energy re-

1. Worldwide, the EIA estimates in their International Energy Outlook 2019 that residential electricity use accounts for roughly 23% of all electricity use, and this is projected to increase to nearly 50% by 2050. Renewables (excluding solar) account for roughly 25% of world generation, and this is predicted to increase to nearly 50% by 2050; the majority of this

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ported in 2018 that renewable electricity grew to 20.5% of installed capacity, and continues to grow with renewables accounting for 42.9% of the new capacity additions in 2018.

Certainly a key contributing factor to the continued growth in renewable energy infrastructure has been supply-side increases arising from energy policy and regulatory reform (e.g., Renewable Portfolio/Electricity Standards, Clean Power Plan, Renew300, and Green Power Partnership).[2] That said, increasing consumer demand for "green" power—stemming from its environmental benefits and sustainability—has also played an important role.[3] Prior research suggests that people express a preference for green power (Greenberg, 2009), and consumers are often willing to pay a *green premium*, typically in the range of \$5-\$15 per month (Menegaki, 2008; Sundt & Rehdanz, 2015). As a result, residential consumers have been increasingly offered the option to participate in voluntary green-power programs (Clark et al., 2003; Bird & Sumner, 2010; and Dagher et al., 2017 for discussion). As of 2018, the National Renewable Energy Laboratory (NREL) reported that 6.3 million customers procured 134 MWh of renewable energy through voluntary green plans, which represented about 28% of non-hydro renewable energy generation in the U.S, but only 3% of total retail electricity sales. Moreover, the take-up rate of voluntary green plans remains relatively low, conservatively estimated at less than 5% (e.g., O'Shaughnessy et al., 2016). Given the increased availability of green plans and the public policy driven expectations of green electricity use, it is important to think about possible mechanisms to increase take-up. Such insights can be valuable for renewable-energy policy, as more stringent emissions standards increase the focus toward green power, as well as for the operational strategies of electric-utility providers in response to renewable electricity generation becoming more cost effective.

The aim of this study is to empirically examine how non-price, information "nudges" about the energy efficiency, production/social costs, and environmental impacts of different electricity-generating sources impact consumers' preferences for green power.[4] We conduct a stated-preference, choice experiment administered via online survey, where respondents make a series of hypothetical choices between a green-power plan and a conventional "gray-power" plan.[5] Prior to making their stated choices, we systematically vary whether individuals receive: (i) positive or negative information about the gray plan, (ii) positive or negative information about the green plan, (iii) a combination of positive or negative information about both plans, or (iv) neutral information (generic facts about electricity). We also vary the expected monthly green-price premium, which enables us to quantify the size of the information effect relative to the pure-price effect. Lastly, we

increase primarily being driven by increases in wind and solar production, estimated to account for over 70% of renewable electricity generation by 2050 (https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf).

2. We refer readers to the American Wind Energy Association (http://www.awea.org/advocacy/) for a discussion of these policies, as well as papers by Bird et al. (2005), Menz (2005), Menz & Vachon (2006), Vachon & Menz (2006), Gan et al. (2007), Fowlie et al. (2014), and Hollingsworth & Rudik (2019) for more detailed discussions surrounding the various policies and regulatory reforms aimed at promoting growth in renewable energy.

3. In our paper we use "renewable" and "green" somewhat interchangeably, although we realize the two categories are not identical; namely, nuclear is often viewed as green and not renewable, while hydro is often viewed as renewable but not green. As will become evident in the exposition of our experimental design, we only consider wind and solar, which are both considered green and renewable and are the fastest growing within both categories; hence, we side-step the potential issues related to merits of nuclear and hydro which are more openly debated compared to wind and solar.

4. Thaler & Sunstein (2008) define a nudge as a change in the choice architecture that can predictably alter behavior without forbidding available options or significantly changing the economic incentives. The information intervention we consider falls into this category as it doesn't restrict the choice set or change the associated cost of any plan.

5. For the gray-power plan, the source is hydrocarbon based. We note that in the actual experiment we referred to this plan as the "conventional" plan, rather than the "gray" plan, to avoid possible negative connotations associated with this labeling. However, for ease of exposition, we refer to this plan as the gray plan throughout the paper.

consider how existing participation in a green plan, personal attitudes toward the environment and green energy, and other socio-demographic measures impact plan choice, as well as their possible moderating role on the information effects. Importantly, an advantage of using a choice experiment is our ability to systematically vary the provision and framing of plan information and, hence, our ability to consider several different information conditions; when combined with a sizable and diverse sample of respondents, this approach can provide robust inferences of the plausible, relative impacts of information nudges on voluntary green-plan adoption.

Based on results from 1,838 respondents over two distinct samples and 21,384 plan-choice scenarios, we find that nudging respondents with information about the attributes relating to the electricity-generating source significantly impacts stated choices. Specifically, providing *pro-green* information (*advantages* of green and/or *disadvantages* of gray) significantly increases green plan selection by roughly 18%–26% relative to the baseline rate of green plan selection with *neutral* information. Conversely, *pro-gray* information (*disadvantages* of green and/or *advantages* of gray) significantly decreases green plan selection by roughly 11%–18% relative to the baseline rate. Importantly, our main results are generally robust across different levels of monthly price premium for the green plan. Although, we do find that promoting the advantages of the green plan is relatively more effective at increasing green plan selection when the green price premium is small, while promoting the disadvantages of the gray plan is relatively more effective when the green price premium is large. Interestingly, we also find that providing disadvantageous information about the green plan can really reduce its selection when the green price premium is large. Moreover, the estimated magnitude of the information intervention is economically meaningful, as it is proportional to the estimated change in green plan selection that would result from a $4 change in the monthly price premium of the green plan.[6]

We also find that different "types" of respondents react differently to the information intervention. In particular, more educated respondents appear to be more sensitive to pro-green information and less sensitive to pro-gray information; thus, more educated people are more "nudge-able" into selecting the green plan. In terms of environmental attitudes, respondents who report being more pro-environmental are less responsive to the pro-green information and more responsive to the pro-gray information; the implication here is that respondents who are more concerned with the environment are less inclined to choose the green plan after receiving some information that the green plan is not all that good, or that the gray plan is not all that bad. Lastly, we find that respondents who report already being a participant in a green-power plan (at their current electric utility) effectively show no significant response to either the pro-green or pro-gray information; this suggests that this type of information intervention nudge might be more effective when targeted toward conventional gray plan participants or new customers.

Prior research has documented many factors that can motivate people to engage in pro-environmental behaviors and the purchase of green-energy products (see Steg & Vlek, 2009; Herbes & Ramme, 2014; Steg et al., 2014 for a review). Among the various factors, psychological motivations can be important, which provide a plausible channel through which information interventions could impact plan choice. Steg & Vlek (2009) discuss how informational strategies, which they define as "being aimed at changing perceptions, motivations, knowledge, and norms, without actually changing the external context in which choices are made" (p. 313), can be instrumental in promoting pro-environmental behavior by "targeting" psychological motivations. Regarding power-plan

6. For context, most voluntary green plans advertise a price premium in the range of $5-$15/month. According to the EIA, monthly residential electric bills in 2018 averaged $117.65 for the entire U.S, with the range across states being $77.25 (Utah) to $165.13 (Hawaii), (https://www.eia.gov/electricity/sales_revenue_price/pdf/table5_a.pdf).

decisions, we argue that providing salient information about the advantages of a certain plan (or the disadvantages of the alternative plan) can be persuasive by appealing to these psychological motivations, ultimately impacting plan choice. Moreover, the efficacy of these information interventions ought to be relatively large in the choice between green and gray plans, compared to other energy choice domains, since choosing to participate in the green plan is relatively convenient and inexpensive (Steg & Vlek, 2009; Steg et al., 2014).

Our study contributes to the recent and growing literature focusing on how non-price nudges can influence energy consumption behaviors (e.g., Allcott & Mullainathan, 2010; Croson & Treich, 2014; Kunreuther & Weber, 2014; Allcott, 2016; Liebe et al., 2018 for reviews). Much of this research has focused on conservation efforts and usage behaviors (i.e., *how much* is consumed). We complement this literature by considering how information nudges can impact people's preceding decision of whether to participate in voluntary green-power programs (i.e., *what type* is consumed). Given the focus of governments and other regulating bodies to reduce GHG emissions and curb global warming, it is important to think about feasible methods to promote growth in renewable energy. As such, within the residential sector, not only must we consider how nudges can impact energy conservation, but also how they can impact plan selection. While conventional economic levers (e.g., lowering prices, altering incentives, imposing regulation) can be effective in increasing the adoption of green plans, such levers can be costly and inefficient from a total welfare perspective.[7] Our results suggest that, as an alternative, nudging in the form of providing targeted information about the advantages of renewable power and/or the disadvantages of conventional gray-power can sizably increase the take-up of voluntary green-power plans; moreover, such information interventions could likely be implemented with more political ease, at a relatively low cost, and without some of the inefficiencies and choice constraints associated with conventional economic policies. Thus, our study is an important contribution to the possible applications of using nudges to motivate consumers to make more environmentally friendly energy decisions.

From a green-power marketing standpoint, utility companies have the ability to advertise different factors associated with their green-power plans, and often do provide information to potential customers about the advantages of their green-power plans (Herbes & Ramme, 2014).[8] Relatedly, some prior studies have examined the role of certification or accreditation as a potential mechanism for marketing green plans (e.g., Dagher et al., 2017; Xie & Zhao, 2018; MacDonald & Eyre; 2018). The idea being that such programs provide a clear and salient signal to potential customers about the merits of the green plan, which can then foster trust and confidence in consumers and, thus, increase take-up. A natural and important question arises as to whether, and the extent to which, different information marketing approaches and/or "eco-labeling" of such plans are effective at stimulating demand. Much of the prior work in this area is observation in nature; hence, there are potential endogeneity and identification issues that make causal inference challenging (as MacDonald & Eyre; 2018, p. 189 discuss).[9] In our study, we directly manipulate the information respondents receive in a randomized manner, which provides some plausible causal inference about the efficacy of information provision in altering plan choices.

7. See Madrian (2014) and Loewenstein & Chater (2017) for more discussions regarding conventional economic policy interventions, and the possible advantages and benefits of using non-conventional nudges to shape behavior.

8. Casual observation of plan webpages found on the Green-e, green-power certified programs (https://www.green-e.org/), reveals many utilities within the U.S. provide information on the benefits of their green-power plans.

9. Specifically, MacDonald & Eyre; 2018 note that one potential issue is the direction of causality is not obvious. It could be that providing eco-labeling information about the plan could increases take-up, or it is a product of increased take-up. Additionally, there is little to no systematic variation in how or what information is presented in these plans, which also makes identification challenging.

2. REVIEW OF RELATED LITERATURE

We focus our review primarily on the existing literature related to residential electricity usage and the adoption of green power, as this most closely relates to our study. In addition, we also review the literature on non-price interventions–nudges–in the domain of energy consumption.

The clear focus of regulating bodies on promoting renewable electricity, in combination with the greater availability of voluntary green-power plans offered by utilities, has garnered substantial research attention aimed at identifying factors that influence consumer demand and take-up of such plans. Not surprisingly, much of the prior research has focused on the role of the price premium. Even less surprisingly, many studies have found that the price premium is an important determinant in consumers' decisions to adopt a green-power plan, with higher price premiums resulting in lower adoption (e.g., Menegaki, 2008; Ma et al., 2015; and Sundt & Rehdanz, 2015 for reviews of this literature).[10] That said, using various techniques and sampling procedures, most prior studies in this domain tend to consistently estimate a positive willingness to pay (WTP) among residential consumers to purchase plans where (at least some of) the power is generated from renewable sources.[11] While the WTP estimates vary across studies (Sundt & Rehdanz, 2015), they tend to be clustered in the range of $5-$15 per month. The results from our survey indicate that 37% of all plan choices were for the green plan when the price premium ranged from $5-$15, which is generally consistent with the findings of these prior studies.

Besides the price premium, prior studies have also documented other factors relating to the plan attributes and consumer characteristics that can impact preferences toward adopting green power (see Oerlemans et al., 2016; MacDonlad & Eyre, 2018 for a review). In terms of plan attributes, the following have been shown to impact preferences for adopting green power plans: the specific type of generating source (e.g., wind, solar, biomass, hydro, etc.) (Borchers et al., 2007; Kaenzig et al., 2013), environmental and wildlife impact (Bergmann et al., 2006), price volatility of the plan (Cardella et al., 2017), and receiving certification/accreditation (Dagher et al., 2017; MacDonald & Eyre; 2018; Xie & Zhao, 2018). In terms of consumer characteristics, Ek (2005) finds that individuals who are more environmentally conscious have a more positive attitude toward wind power, and Clark et al. (2003) and Kotchen & Moore (2007) find that pro-environmental respondents were more likely to have enrolled in a green power program, while Mozumder et al. (2011), Oliver et al. (2011), Cicia et al. (2012), Gracia et al. (2012), and Amador et al. (2013) find that more environmentally conscious people have a higher WTP for green power. Income has also been shown to be positively related to preferences and willingness to pay for green power adoption (Clark et al., 2003; Borchers et al., 2007; Kotchen & Moore, 2007; Longo et al., 2008; Bollino, 2009; Yoo & Kwak, 2009; Mozumder et al., 2011; Oliver et al., 2011; Conte & Jacobsen, 2016), as well as higher levels of education (Tabi et al., 2014; Conte & Jacobsen, 2016) and urban versus rural (Bergmann et al., 2008).

10. Wiser et al. (2005), Mewton & Cacho (2011), Conte & Jacobsen (2016), and Dagher et al. (2017) use actual plan participation data to estimate the impact of price premiums on green participation behavior (among other factors of interest) and find that price premium negatively impacts green participation, and demand is relatively price inelastic.

11. For example, Goett et al. (2000), Roe et al. (2001), Borchers et al. (2007), Longo et al. (2008), Scarpa & Willis (2010), Cicia et al. (2012), Gracia et al. (2012), Kaenzig et al. (2013), and Cardella et al. (2017) use choice experiments to document a positive WTP for green power. Similarly, Champ & Bishop (2001), Zarnikau (2003), Whitehead & Cherry (2007), Wiser (2007), Diaz-Rainey & Ashton (2008), Bollino (2009), Yoo & Kwak (2009), Mozumder et al. (2011), and Oliver et al. (2011) use contingent valuation approaches to document a positive WTP for green power (Oerlemans et al., 2016 review this literature and conduct a meta-analysis).

More recently, there has been a growing interest in how non-price interventions, or nudges, can influence energy consumption behavior.[12] Much of this literature focuses on end usage of residential consumers and possible mechanisms for fostering conservation behavior. Informative discussions of these different types of interventions and their effectiveness, and reviews of the relevant literature, are provided by Abrahamse et al. (2005), Steg (2008), Steg & Vlek (2009), Allcott & Mullainathan (2010), Croson & Treich (2014), Kunreuther & Weber (2014), and Allcott (2016).[13,14] More in the spirit of the type of nudge we consider in our study, several papers have examined the impact of various types of information provision on energy conservation behavior and other pro-environmental behaviors. For example, Asensio & Delmas (2015) find that providing information about negative health effects and pollution associated with electricity production reduces household usage. Ito et al. (2018) find that "moral suasion" in the form of providing a motivational information statement that conservation is needed during peak times leads to lower usage. Reiss & White (2008) and Costa & Gerard (2020) find that public campaigns calling for conservation are effective in reducing residential electricity usage.[15] Ek & Soderholm (2010) find that providing information about cost savings associated with energy conservation does result in less energy use, while Gilbert & Zivin (2014) document a similar finding where sending spending reminders to the household decreases usage. Ungemach et al. (2017) find that providing information about the environmental attributes of a car (i.e., greenhouse gas rating) increases the likelihood of choosing a more fuel-efficient car. These prior studies suggest that providing information in a variety of different forms can influence energy consumption behavior.[16] That said, these prior studies have focused on usage and conservation efforts, while our study complements this prior work by examining how information impacts the upstream decision of households on whether to opt into participating in a voluntary green-power plan.

We are aware of a few prior studies that have looked specifically at how non-price interventions can impact plan choice. Most closely related to our study, Momsen & Stoerk (2014) use a choice experiment to examine the impact of several different types of nudges (e.g., priming, mental

12. The growing research interest in how, and the degree to which, nudges can impact behavior spans beyond energy consumption behavior. There is substantial literature on how nudges can impact behavior across a host of other domains, including, but not limited to: water conservation, financial planning, retirement planning, education, healthcare, and risky behaviors. We refer interested readers to Johnson et al. (2012), Madrian (2014), Benartzi et al. (2017), Loewenstein & Chater (2017), and Loewenstein et al., (2017) for interesting discussions and reviews of this literature.

13. Providing usage feedback (typically through smart metering) has been shown to promote conservation behavior (e.g., Gans et al., 2013; Houde et al., 2013; Schleich et al., 2013; Jessoe & Rapson, 2014; and Delmas et al., 2013; Ramos et al., 2015 for reviews). Providing users with information about peer consumption and cues of social norms has also been shown to be effective in reducing energy consumption (e.g., Schultz et al., 2007; Allcott, 2011; Ayres et al., 2013; Costa & Kahn, 2013; Allcott & Rogers, 2014; Delmas & Lessem, 2014; Ho et al., 2016; Allcott & Kessler, 2019; see Abrahamse & Steg, 2013 and Ramos et al., 2015 for reviews). Setting usage goals is also effective in reducing usage (e.g., McCalley & Midden, 2002; Abrahamse et al., 2007; Loock et al., 2013; Harding & Hsiaw, 2014).

14. A body of literature also exists documenting how usage feedback, peer comparisons, and norm appeals impact residential water conservation (e.g., Ferraro et al., 2011; Ferraro & Price, 2013; Bernedo et al., 2014; Brent et al., 2015; Goette et al., 2019).

15. Cutter & Neidell (2009) document a similar effect relating to public transit use where the "Spare the Air" campaign in the San Francisco Bay Area decreased traffic volume and increased public transit use. However, Holladay et al. (2015) find little evidence that appeals for conservation efforts reduce energy usage and CO_2 emissions.

16. There is a body of literature looking at the effect of energy-efficient labeling (e.g., Energy Star) on consumer purchase behavior (see Banerjee & Solomon, 2003 for a review). Generally, this research suggests that labeling products as more energy efficient and/or cost effective increases the willingness to pay for such appliances (e.g., Shen & Saijo, 2009; Ward et al., 2011; Houde, 2018) and, ultimately, the adoption of such appliances (Newell et al., 1999; Sanchez et al., 2008; Newell & Siikamäki, 2014).

accounting, framing, decoy effects, social norms, and defaults) on green plan selection. Of particular relevance, one of their implemented nudges involves *subtly* priming respondents by asking them to either write down everything they know about the link between energy production and climate change, or re-assemble statements about the same relationship; they find that this pre-intervention does not increase take-up of the green plan. They find that only the default nudge of having the green plan pre-selected increases take-up. This is consistent with the studies by Pichert & Katsikopoulos (2008), Sunstein & Reisch (2013), Ebeling & Lotz (2015), and Ghesla (2017) who also find that defaulting participants into the green plan increases participation.

In our study, we examine how providing direct and salient information about the advantages and/or disadvantage of the plans impacts green plan selection, which more closely resembles the marketing efforts of many utilities offering voluntary green plans and other green marketing organizations. In doing so, we complement the existing literature aimed at deepening our understanding of factors that can impact residential demand for green power. Additionally, our paper considers another application—participation in green power programs—of how non-price nudges can be used to influence energy choices and promote pro-environmental behavior (Liebe et al., 2018).

3. EXPERIMENTAL SURVEY DESIGN

We designed an online choice experiment, which was developed and administered through Qualtrics. A detailed description of the experimental protocol with a copy of instructions is provided in Supplemental Appendix A. In total, 1,838 respondents completed the experiment. Prior to making their plan choices, respondents systematically received different information about the electricity generation of either one or both plans. This enables us to empirically identify the impact of the provided information on the take-up rate of the green plan. After completing the plan choice scenarios, respondents completed a short demographic and attitudinal questionnaire.[17]

3.1 Choice Experiment of Electric Power Plan

In the choice experiment, respondents were simultaneously presented with information on two hypothetical plans offered by an electric utility, and were asked to select which plan they *would* select. This scenario was intended to represent a prospective customer who needs electricity and is, thus, required to choose one of the two plans offered; in this regard, an explicit opt-out option is not in the choice set. For each plan, respondents received information about: (i) generating source of the electricity, and (ii) average expected monthly price. A sample choice set is presented in Figure 1.[18]

17. Importantly, and as we would expect, a post-hoc examination reveals virtually no differences in the measured respondent demographics, characteristics, and attitudes across the different information manipulations. Specifically, a series of ANOVA tests reveals no statistically significant effects of the information manipulation on any of these collected measures. As such, our randomization to information manipulation was successfully achieved.

18. As part of a separate research project, Cardella et al. (2017), we also manipulated the monthly price volatility as an attribute of each plan. Monthly price volatility was presented in the form of a price distribution table that displayed the possible monthly prices and the corresponding percent chance of each price occurring, as depicted in the sample choice set in Figure 1. In total we considered five different price volatility manipulations, which are reproduced in Appendix E. Given the primary research question of this study, we collapse the price volatility dimension of the choice set and present results that are aggregated over the different price volatility levels. However, our main results presented in Section 4 are robust if we disaggregate the data and look at the informational effects within each level of price volatility; in other words, the monthly price volatility of the plan does not moderate the informational effects. Many voluntary green plans advertise an average monthly price premium so it is implicit that there is some price volatility. Furthermore, the supply of green power sources is inherently more variable than conventional sources, which should be expected to increase price variability for the consumer. In our study

Figure 1: Sample Choice Scenario

PLAN A – CONVENTIONAL ELECTRICITY	
Generating Source: Coal or Natural Gas	
Possible Monthly Price	**Chance of Price**
$95	5%
$100	90%
$105	5%
Average Expected Monthly Price: $100	

PLAN B – GREEN ELECTRICITY	
Generating Source: Wind or Solar	
Possible Monthly Price	**Chance of Price**
$90	40%
$105	20%
$120	40%
Average Expected Monthly Price: $105	

The two plans were labeled **Plan A—Conventional Electricity** and **Plan B—Green Electricity.** All choice scenarios were presented in an identical format. The generating source for the conventional plan was described as being produced by either coal or natural gas (or presumably a mix), while the generating source for the green plan was described as being produced by either wind or solar (or presumably a mix). We choose to display the green plan as a (possible) mix of wind and solar since consumers generally have a more positive attitude about these two sources, many electric utilities advertise a mix of generating sources for their green plans, and the EIA reports that a majority of future growth in renewables will be accounted for by wind and solar.[19] Moreover, by presenting the plan as a mix, we reduced the likelihood that results are specific to a specific type of renewable energy source.

Each choice set consisted of one gray plan and one green plan option. Across choice sets, the average expected monthly price for the green plan was either: (i) $105/month, (ii) $110/month, or (iii) $115/month, while the average expected monthly price for the gray plan was always normalized to $100/month;[20] thus, the monthly premium of the green plan is either $5, $10, or $15, respectively. These specific values of the price premium were chosen to be consistent with actual observed and documented average premiums of green power programs (Bird et al., 2002; Bird & Sumner, 2010; MacDonald & Eyre, 2018), as well as within the general range of estimated willingness to

we simply make this volatility explicit via the presentation of a pricing distribution. But to ensure the average monthly price is salient, we provide that information in the description of the plan. While this opens the door for risk preferences to play a role in the plan decision, our between treatment comparisons of the impact of the pre-information intervention remains valid under the rather innocuous assumption that risk preferences do not interact with the information manipulation.

19. Previous work by Ek (2005), Borchers et al. (2007), Gracia et al. (2012), Kaenzig et al. (2013), Ma & Burton (2016), and Bae & Rishi (2018) suggests that consumers generally have a more positive attitude about these two sources of renewable energy generation; thus we circumvent possible issues arising from the potential mixed opinions relating to nuclear and hydro. Second, inspection of the 49 Green-e certified residential renewable electricity programs across the U.S. (https://www.green-e.org/certified-resources) reveals that 18 are 100% wind, 14 are 100% solar, and 15 are a mix of generating sources. Given that 74% of the plans listed are comprised entirely of wind and solar and 92% being at least 50% wind or solar, presenting our hypothetical green plan as being a mix of wind and solar seems representative and appropriate. Lastly, the EIA reports that increases in global renewable electricity production over the next several decades will be driven largely from increases in wind and solar generation – estimated at over 70% of electric generating capacity by 2050 (https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf)

20. The EIA reported that in 2017, average US household electricity usage was 867 kWh/month. At an average cost of $.12/kWh, this would put average monthly expenditure at $104/month. As such, we feel $100/month as the baseline monthly rate for the gray plan is very representative of what participants in our sample would be accustomed to.

pay for green power (e.g., Roe et al., 2001; Zarnikau, 2003; Borchers et al., 2007; Wiser, 2007; and Mozumder et al., 2011).[21]

We implemented a blocked, orthogonal, fractional factorial design with 48 distinct choice sets divided into four blocks of 12 choices.[22] Respondents were randomly assigned to one block and presented with all 12 corresponding choice sets, one at a time. Respondents were asked to choose their preferred plan in each choice set, from which we estimated the main effects.

3.2 Plan Information Manipulation

The main manipulation involved the information respondents received prior to the plan-choice experiment. Before viewing the choice scenarios, we provided respondents with *six* information statements pertaining to either the *advantageous* or *disadvantageous* attributes associated with generating electricity from the given source. The statements centered on environmental impacts, relative costs, production efficiency, and health impacts. The idea was that advantageous information was meant to frame that corresponding plan in a positive light, while disadvantageous information was meant to frame that corresponding plan in a negative light. A list of the specific information statements that were used is provided in Supplemental Appendix B.

For the green plan, the advantageous information statements include: its non-depleting nature, its non-emission of greenhouse gases or other air pollutants, its reduced dependence on foreign oil trade, and its non-dependence on fresh water resources; the corresponding disadvantageous statements include: its intermittency, its large land requirements that can disturb ecosystems, its difficulty to store, and its relative inefficiency and higher cost. Conversely, for the gray plan the advantageous information statements include: its abundance, its continuous production, its relative low cost, its ease of storage, and its relative efficiency; the corresponding disadvantageous statements include: its nonrenewable properties, its generation of greenhouse gases, its environmental damages, and possible health hazards.

Lastly, we also had a condition where respondents were presented with *neutral* information in the form of *six* generic statements about energy and electricity including: average electricity usage per household, transmission and distribution, and prices. We refer to this condition as the *Baseline.* The *Baseline* condition establishes the benchmark level of green plan selection in our sample, around which we can then evaluate the effect of the main information conditions on the selection rate of the green plan. Importantly, the *Baseline* condition also provides information to respondents prior to their plan choices. In this regard we hold constant the possibility that providing respondents with *any* information may somehow make them more reflective in their choices, which allow for a more apples-to-apples comparison between the *Baseline* and other main information conditions; thus providing cleaner identification of the main treatment effects of interest.

We implemented a between-groups design where respondents were randomly assigned to one of the possible information treatments (including the Baseline), which are outlined in Table 1.[23]

21. Furthermore, inspection of green-power programs certified by Green-e (https://www.green-e.org) and listed on their website reveals that most programs advertise a price premium of the green plan in the range of $5-$15/month, with an estimated base rate of $100/month for a standard customer.

22. Our main-effects, full factorial design, consisted of $3 \times 5 \times 5 = 75$ choice sets, which included the three price premiums and five possible price-volatility levels for each of the plans as described in Footnote 17. The FACTEX and OPTEX procedures in SAS v9.4 were used to generate the orthogonal, fractional factorial design.

23. For completeness of the full factorial design, we had two additional conditions that provided positive information about both the green and gray plan (*PosGreen+PosGray*) *or* negative information about both the green and gray plan (*NegGreen+NegGray*). In essence, these conditions could be viewed as "ambiguous", as they either promote both plans or dissuade both plans. Given that these condition have *offsetting* information statements, we anticipated no impact of these condi-

The four single information conditions—*PosGreen, NegGreen, PosGray, NegGray*—allow us to investigate the impact of providing targeted information on the attributes of the generating source of energy for one plan. Intuitively, the *PosGreen* and *NegGray* conditions are “pro-green” nudges that are targeted toward promoting the selection of the green plan. Conversely, the *NegGreen* and *PosGray* conditions are “pro-gray” nudges that are targeted toward promoting the selection of the gray plan. Regarding the two dual-information conditions—*PosGreen+NegGray, NegGreen+PosGray*—we are interested in whether there is a cumulative effect. Specifically, for the *PosGreen+NegGray* condition, is there a cumulative pro-green nudge effect that may increase green plan selection relatively more than just *PosGreen* or *NegGray*. Likewise, for the *NegGreen+PosGray,* is there a cumulative pro-gray nudge effect that may decrease the selection of the green plan relatively more than just the *NegGreen* or *PosGray* conditions.

Table 1: Description on Information Conditions

Treatment Name	Information on Green Plan			Information on Gray Plan			Treatment Category
	None	**Positive**	**Negative**	**None**	**Positive**	**Negative**	
Baseline	✓			✓			Neutral
PosGreen		✓		✓			*Pro-Green*
NegGreen			✓	✓			*Pro-Gray*
PosGray	✓				✓		*Pro-Gray*
NegGray	✓					✓	*Pro-Green*
PosGreen+NegGray		✓				✓	*Pro-Green*
NegGreen+PosGray			✓		✓		*Pro-Gray*

We acknowledge that the six statements likely do not describe all attributes associated with electricity production from the given source. That said, our aim was to provide information that highlighted either the possible advantages or disadvantages of electricity generation from renewable green power generation or conventional gray power generation; moreover, we included information about several different attribute domains. As such, we can gain insights into how either the promotion of the green plan and/or dissuasion of the gray plan (and vice versa) impacts the overall adoption of voluntary green-power plans. Importantly, by also varying the price premium of the green plan across choices, we are able to compare the magnitude of the information statements effects relative to the magnitude of the price impacts.

3.3 Information Manipulation Check

It is important to first verify that the information conditions impacted perceptions of the plans in the intended ways. To do so, we recruited an independent student sample of 136 respon-

tions on selection of the green plan. However, our motivation in including these conditions was to allow for the possibility that respondents perceive these offsetting information statements in a systematically biased way; for example, as being relatively more positive toward the green plan (when positive information is provided about both plans) or being relatively less negative toward the green plan (when negative information in provided about both plans). However, ex-post examination of the data revealed these two ambiguous conditions had little impact on selection of the green plan, confirming our initial supposition. Specifically, there are no significant differences in green plan selection between these two conditions and the *Baseline*. We include these two conditions in all regression analyses, but for brevity, they are omitted from the main results. All regression results are robust if we, instead, omit these conditions. The summary statistics (Figure 2.A1) and analysis (Table 2.A1) from these two conditions are provided in Appendix D.

dents (who did not participate in the choice survey) to evaluate the statements. A detailed description of the procedure and additional results are presented in Supplemental Appendix C.

For the six neutral statements that comprised the *Baseline* condition, we asked respondents to rate whether each statement supported hydrocarbon electricity or green electricity. Responses were on a 7-point Likert scale (1=supporting hydrocarbon electricity; 4=neutral; 7=supporting green electricity). For each respondent we averaged their responses over the six statements to generate a composite rating; the mean composite rating was 3.63 and the median was 3.83, suggesting these six *Baseline* statements pertaining to general electricity facts were indeed viewed as being relatively neutral, as intended.

We implemented a similar approach for validating the information statements pertaining to the green and gray plans. Participants were either presented with all the information statements about the green plan or the gray plan (in random order), and then asked to indicate whether the statement was a positive or negative property. Responses were, again, on a 7-point Likert scale (1=very negative; 7=very positive). The six statements comprising the *PosGreen* condition had an average composite rating of 5.70, while the six statements comprising the *NegGreen* condition had an average rating of 2.90. Importantly, these averages are both significantly different from the neutral scale rating ($p < .001$ in both instances). The six statements comprising the *PosGray* condition had an average composite rating of 5.41, while the six statements comprising the *NegGreen* condition had an average rating of 2.33. Again, both of these averages are significantly different from the neutral scale rating ($p < .001$ in both instances). Based on the responses from the sample of independent evaluators, the information manipulations were effective at conveying the desired information: (i) the set of advantageous information statements about the green plan or the gray plan were, in fact, evaluated positively; (ii) the set of disadvantageous information about the green plan or the gray plan were, in fact, evaluated negatively.

3.4 Participant Sampling

Our survey utilized two distinct samples. Data was collected from February 2016 to February 2017. The first sample is a nationally representative panel generated by Qualtrics Panels, LLC. For this sample, we restricted participation eligibility to individuals responsible for paying their electricity bill. After the initial screening, this sample consisted of 1,150 respondents (79% overall response rate): 69% were female, a median age range of 35–44 years, and over 900 distinct zip codes from 45 states were reported. The second sample consists of business school students. Participants were recruited via email from a large database who enroll to participate in research studies, for which they receive research credits. A total of 688 students completed the survey: 50% were female, the median age range was 18–24 years. The students were not required to be responsible for paying their own electricity bill, although we did ask respondents this question, and 64% indicated in the affirmative. Considering a separate student sample, in addition to a more representative sample of adult utility customers, is useful since students represent the next generation of electric utility consumers; hence, better understanding their (potentially different) attitudes and behavior toward green-power adoption, is crucial for informing policy aimed at stimulating the adoption of green-power alternatives and predicting future trends of residential electricity consumption.[24] Together, the

24. Additionally, Gossling et al. (2005) document evidence that students generally have a positive attitude toward green power, which suggests they may be the population most likely to consider green-power alternatives. Relatedly, Mills & Schleich (2012) find that university education increases the stated importance of energy conservation. Therefore, students might be the most susceptible to information nudges aimed at promoting green power.

results from two distinct samples provides more robust inferences regarding the impact of providing informational nudges on the adoption of voluntary green-power plans.

4. RESULTS

For each respondent, we observe their plan choice for each of the 12 choice sets.[25] All respondents were treated with one of the possible information conditions outlined in Section 3.2. Our primary focus is on estimating how these informational nudges impact the respondents' choice of the green plan.

4.1 Comparison of Qualtrics Panel Sample and Student Sample

Recall, our survey utilized two distinct samples: (i) a representative Qualtrics panel of 1,150 respondents, and (ii) the student sample of 688 respondents. Aggregated over all choices, respondents from the Qualtrics panel chose the green plan 36.9% of the time, while respondents from the student sample chose the green plan 37.3% of the time; this difference is not statistically different (t-test: $p = .773$).[26] In addition, a factorial ANOVA reveals no significant main effect of the student sample ($p = .807$) or interaction between the student sample and the information condition ($p = .516$) on green plan choice. In our view, this is sufficient to conclude that there are no concerning sample differences with regard to respondent behavior. As a result, we pool the data for the remainder of the analysis to provide a larger sample size, additional power, and more robust inference regarding the main results that are gleaned from the response data; when appropriate we control for the type of sample in all regression analyses.[27]

4.2 Effect of Information Manipulation on Green Plan Choice

Figure 2 plots the aggregate percentage of green plan choices across the different information conditions (with error bars representing 95% confidence intervals of the mean). The information conditions are grouped into ***pro-green*** (*PosGreen, NegGray, PosGreen+NegGray*) and *pro-gray* (*NegGreen, PosGray, NegGreen+PosGray*) categories. Everything is in reference to the *Baseline* information condition, which resulted in an aggregate green plan selection rate of 36.2%. Importantly, there are clear impacts of the information conditions on the selection of the green plan, which are jointly significantly different (ANOVA: $p < .001$).[28]

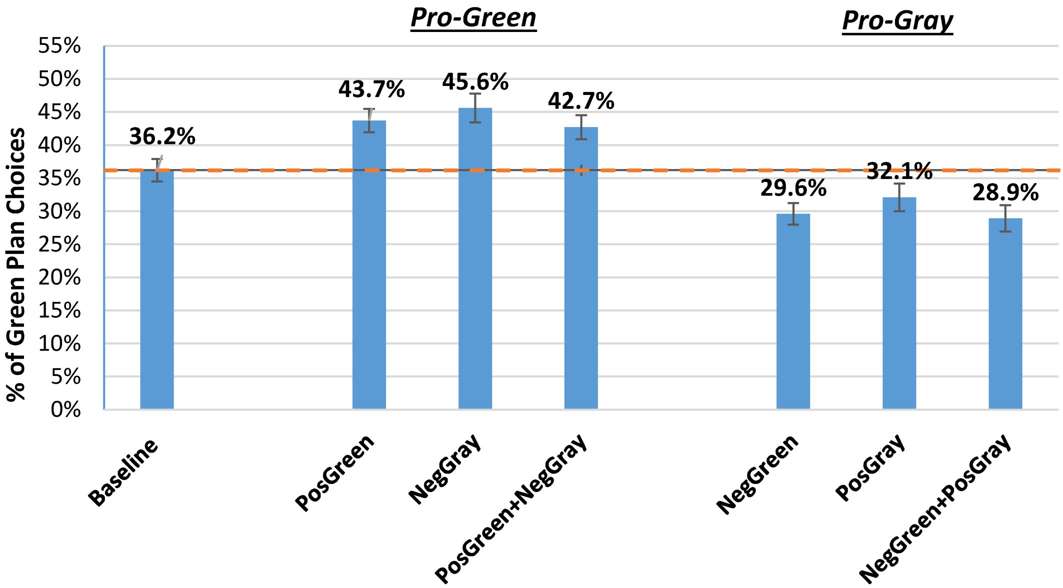
25. As part of IRB compliance, we did not implement forced response. However, 94% of respondents did make a selection in all 12 choice sets. Because of the small fraction of non-responses, we end up with slightly fewer (21,384) observed choices than the total number of all choices sets (1,838 X 12 = 22,056). We include all choice observations in the data, although our results are robust if we include only those respondents that answered all 12 choice sets.

26. Because each subject makes multiple plan choices, we create a subject-level measure that is simply the proportion of choices for the green plan. When necessary, all statistical testing in the remainder of the analysis is performed using this conservative, subject-level measure of green plan choice, which ensures independence of observations. For robustness, we also test for differences in the proportion of green plan choices using a version of the Chi-squared test for correlated data (Donner, 1989); the statistical inferences generally remain qualitatively similar, and any discrepancies that result in non-significance are reported.

27. All our main results regarding the impact of the information conditions on green plan choice are qualitatively robust if we analyze each of the two samples separately. We report the main analysis of treatment effect for just the Qualtrics panel in Table 2.A2 in Appendix D.

28. As part of the post-survey questionnaire, we asked participants if their current electric utility uses any green energy sources, and 308 (16.8%) reported *Yes.* Some, if not all of these respondents may have received information about the ad-

Figure 2: Impact of Information Conditions on Selection of Green-power Plan



Looking first at the *pro-green* information conditions, we see from Figure 2 that all three conditions increased the selection of the green plan. Specifically, 43.7% of choices were for the green plan in the *PosGreen* condition, 45.6% in the *NegGray* condition, and 42.7% in the *PosGreen+NegGray* condition; all three conditions are significantly higher compared to the *Baseline* rate of 36.2% (p = .002, p = .003, p = .031, respectively). Moreover, the difference between the *PosGreen* and *NegGray* conditions is small and insignificant (p = .664), suggesting that both are similar in their effectiveness. Lastly, the proportion of green-plan choices in the *PosGreen+NegGray* is very similar to the *PosGreen* and *NegGray* conditions, which suggests little evidence of a cumulative information effect.

In terms of the three *pro-gray* conditions, we see that each decreased selection of the green plan (i.e., increased selection of the gray plan). The proportion of choices for the green plan were 29.6% in the *NegGreen* condition, 32.1% in the *PosGray* condition, and 28.9% in the *NegGreen+PosGray* condition, although, only *NegGreen* and *NegGreen+PosGray* are significantly different from the *Baseline* of 36.2% (p = .042, p = .032, respectively).[29] Similar to the pattern that emerged with the pro-green condition, we see little difference between the *NegGreen* and *PosGray* conditions (p = .580). Likewise, there appears to be little cumulative pro-gray information effect, if any, as there is no significant difference between *NegGreen+PosGray* and *NegGreen* (p = .595), or *PosGray* (p = .381).

To directly estimate the impact of the information condition, price-premium, and other socio-demographic variables on the likelihood that the green plan is chosen, we estimate a logistic

vantages of green energy from their utility. As such, the information intervention in this study might have been less effective on this subgroup. Importantly, our main results are robust if we exclude the 308 respondents whose current utility uses green energy; Appendix D re-produces Figure 2 excluding all choices made by these 308 respondents (Figure 2.A2), and the baseline rate of green plan choice is essentially unchanged (35.1%); likewise, the change in green plan selection associated with the other information condition essentially mirrors those in Figure 2 for the entire sample.

29. The PosGray condition did not result in significantly fewer green plan choices. We suspect that this weaker effect might have been a result of some over-arching skepticism about positive information related to conventional gray energy. Maybe people are more engrained to view gray energy in a negative way, so it's harder to turn that prior belief.

regression model with green plan choice as the binary dependent variable. To account for the possible serial correlation stemming from multiple plan choices, we clustered standard errors at the respondent level. Table 2 reports the estimated marginal effects for several different specifications.[30] In each specification, the *Baseline* condition is the excluded condition, thus all marginal effects are relative to the *Baseline*.

Looking at Table 2, we see that the estimated information effects generally mirror those depicted in Figure 2. The three *pro-green* conditions all have a positive and statistically significant effect on green plan choice (column 1); moreover, this effect is stable and robust after controlling for a host of respondent characteristics (column 2) as well as the green price premium (columns 3 and 4). In terms of the magnitudes of the effects, the estimated marginal effects in the full model (column 4) range from .058 (for *PosGreen+NegGray*) to .078 (for *PosGreen*). None of the estimated effects across these *pro-green* conditions are significantly different from each other. Our data indicate that nudging respondents by providing information on the advantages of green electricity production and/or the disadvantages of gray electricity production increases selection of the green plan by as much as 7.8 percentage points relative to the *Baseline* condition, which corresponded to a roughly 22% increase from the *Baseline* rate.

In terms of the *pro-gray* conditions, Table 2 reveals that all three have a negative impact on green plan choice, although this estimated effect is significant only for the *NegGreen* and *NegGreen+PosGray* conditions (column 1); furthermore, this pattern is robust across the inclusion of respondent characteristic controls and the price premium (columns 2–4). The magnitude of the estimated marginal effects from the full model are –.052 for *NegGreen* and –.077 for *NegGreen+PosGray* (not significantly different from each other). Thus, nudging respondents with both negative information about green electricity and positive information about gray electricity decreases green plan selection by as much as 7.7 percentage points relative to the *Baseline* condition, which corresponds to a roughly 21% decrease.

Conventional economic theory as well as prior research suggests that the green price premium should be an important determinant in the decision to select the green plan, and our data confirm this. Namely, from columns 2 and 4 of Table 2, we see that the *$10 price premium* and *$15 price premium* indicators both have large and significant negative impacts on green plan choice. The estimated marginal effects imply that moving from a $5/month price premium to $10/month reduces the likelihood of selecting the green plan by 10.9 percentage points, while moving to $15/month reduces the likelihood by 23.1 percentage points. Assuming linearity in the price effect, this implies that each $1 increase in the monthly price premium of the green plan reduced take-up of the green plan by roughly 2 percentage points.

Lastly, we briefly report on the results regarding the respondent characteristics included as controls. Of the included demographic variables—*male, education, income*, and *children*—only *education* and *children* have significant effects; namely, higher levels of self-reported education are associated with an increase in green plan selection, while respondents who report having children are less likely to choose the green plan. Not surprisingly, respondents who reported being enrolled in a plan where at least some of the electricity is generated from a green source, *green plan customer*, are significantly more likely to adopt the green plan. Consistent with prior studies mentioned in

30. We present the results from a logit model with clustered standard errors at the respondent level as our preferred specification, as it allows us to include socio-demographic variables as controls (which do not vary over choices at the individual level). However, our main results regarding the impact of price volatility and price dispersion are robust to alternative specifications, including a probit model and linear probability model. Our main results are also robust and stable if we alternatively estimate a random effects logit, or to the inclusion of respondent fixed effects.

Table 2: Logit Models with Green Plan Choice as Dependent Variable

	Dependent Variable: *Green Plan Choice*			
	1	2	3	4
PosGreen	.073***	.078***	.073***	.078***
	(.027)	(.025)	(.027)	(.025)
NegGray	.092***	.076**	.092***	.076**
	(.033)	(.032)	(.033)	(.032)
PosGreen+NegGray	.065**	.058*	.065**	.058*
	(.032)	(.031)	(.032)	(.031)
NegGreen	–.069***	–.052**	–.069***	–.052**
	(.026)	(.025)	(.026)	(.025)
PosGray	–.039	–.040	–.039	–.040
	(.034)	(.032)	(.034)	(.032)
NegGreen+PosGray	–.074**	–.077**	–.074**	–.077**
	(.034)	(.032)	(.034)	(.032)
$10 Price Premium			–.109***	–.109***
			(.006)	(.006)
$15 Price Premium			–.231***	–.231***
			(.008)	(.008)
Male		–.013		–.013
		(.016)		(.016)
Education		.016***		.016***
		(.006)		(.006)
Income		.005		.005
		(.004)		(.005)
Children		–.045**		–.045**
		(.022)		(.022)
Green Plan Customer		.050**		.050**
		(.025)		(.025)
NEP Scale		.002**		.002**
		(.001)		(.001)
Green Electricity		.080***		.080***
		(.010)		(.009)
Student	.008	–.007	.008	–.006
	(.016)	(.020)	(.016)	(.020)
Block Dummies	Yes	Yes	Yes	Yes
Respondent Clustering	Yes	Yes	Yes	Yes
N	21,384	21,258	21,384	21,258

Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Marginal effects are reported with standard errors in parentheses.
*** significance at 1% level; ** significance at 5% level; * significance at 10% level

Section 2, we do find that pro-environmental attitudes—generally measured using the scale from the 15-item New Ecological Paradigm (Dunlap et al., 2000; Kotchen & Reiling, 2000), *NEP scale*—positively relate to choosing the green plan. We also include a 5-point Likert-scale measure of the importance that electricity be generated in a renewable manner, *green electricity*. This measure also has a positive and significant effect on green plan choice; as we would expect, respondents who think renewable electricity is important are more likely to choose the green plan, all else equal.

Importantly, our data enable us to compare the magnitude of the information nudges relative to the magnitude of the green price effect. In particular, providing pro-green nudges increases selection of the green plan by as much as 7.8 percentage points, while opposite pro-gray nudges can decrease green plan selection by as much as 7.7 percentage points. To put this in relative context, these estimated effects are each roughly equivalent in magnitude to the effect of a $4/month change in the price of the green plan.

4.3 Response to Information Condition Stratified by Price Premium of Green Plan

Next, we examine if, and to what extent, the magnitude of the green price premium impacts how people respond to the information interventions. We disaggregate the choice data by price premium and compare green plan selection across information conditions. For brevity, we focus specifically on the comparison between the lowest price premium (\$5/month) and highest price premium (\$15/month). Figure 3 separately displays the aggregate percentage of the green plan choices across information conditions for the \$5 (Panel A) and \$15 (Panel B) price premiums (with error bars representing 95% confidence intervals of the mean). A factorial ANOVA reveals a highly significant main effect of price premium ($p < .001$) and information condition ($p < .001$), as well as a significant interaction between the premium and the information condition ($p < .001$). In Table 3, we separately report the results for the full logistic regression of green plan choice for \$5, \$10, and \$15 price premium levels.

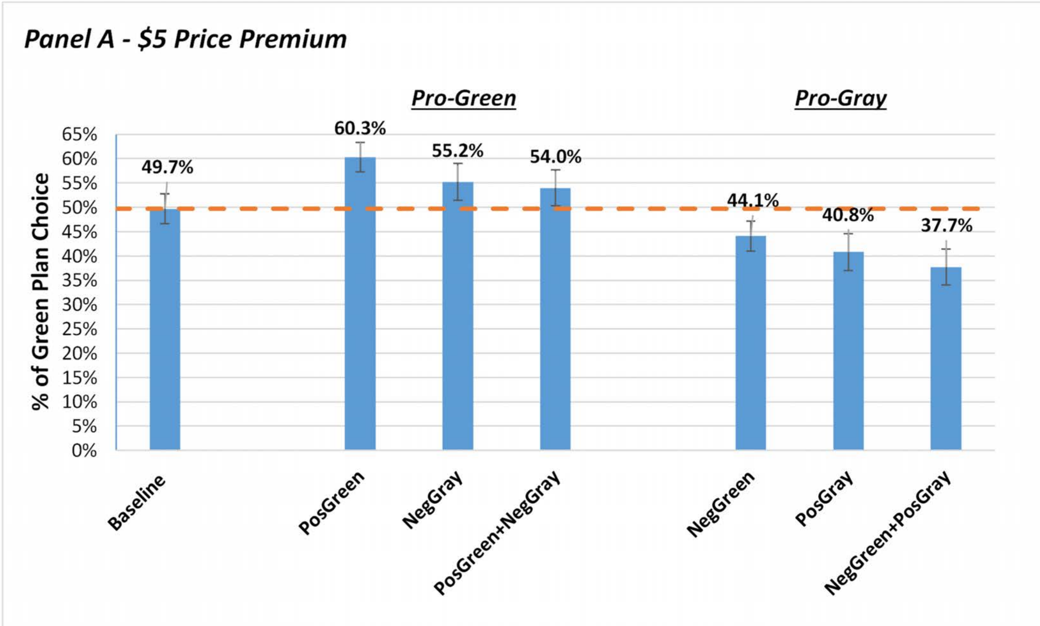
Comparing between the \$5 and \$15 price premiums, we see some differences emerge in terms of the effectiveness of *positive* versus *negative* information. In particular, when the premium is \$15, respondents seem to be relatively more responsive to the negative information. In the *pro-green* case, the *NegGray* condition increased choice of the green plan by 10.2 percentage points from the *Baseline*, while the *PosGreen* condition comparably increased green plan choice by only 3.9 percentage points; this difference is significant ($p = .007$). Moreover, based on the results of the logistic regression reported in Table 3, only the *NegGray* condition indicator enters significantly (and *PosGreen+NegGray* marginally) at the \$15 price premium. Similarly, in the *pro-gray* case, the *NegGreen* condition decreased green plan choice by about 6.8 percentage points from the *Baseline*, while *PosGray* led to essentially no change; this difference is significant ($p < .001$). Table 3 reveals only the *NegGreen* condition indicator loads significantly at the \$15 price premium. Thus, the negative information about either the green plan or the gray plan evokes a stronger behavioral response at the high \$15 price premium for the green plan.

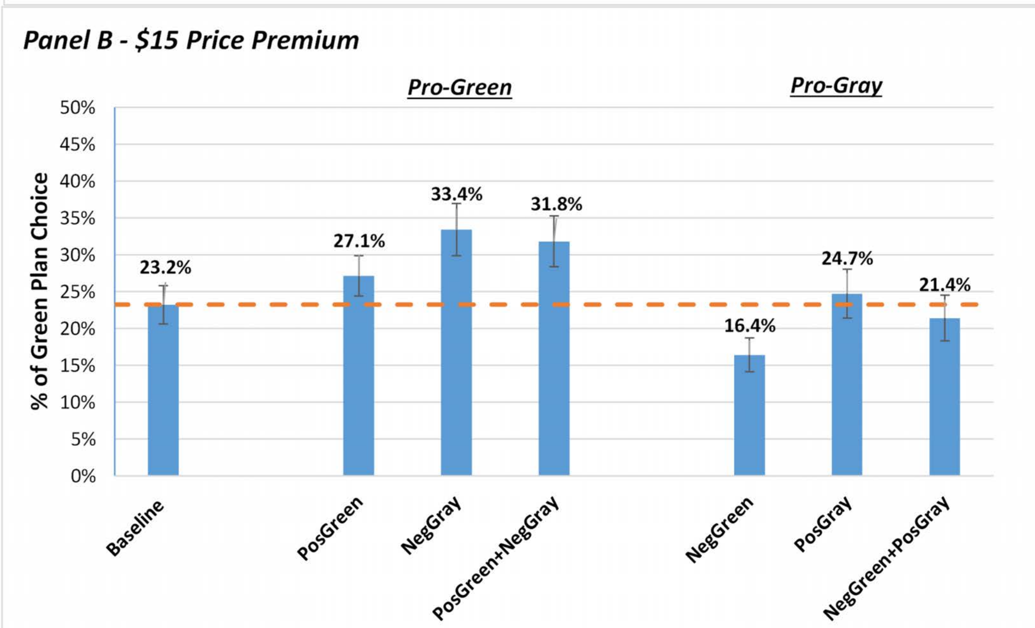
Conversely, at a \$5 price premium, respondents seem to be relatively more responsive to *positive* information compared to the corresponding *negative* information. Specifically, in the *pro-green* case in comparing just positive versus negative, the *PosGreen* condition increased the choice of green plan by 10.6 percentage points, while the *NegGray* condition increased it by only 5.5 percentage points; this difference is significant ($p = .037$).[31] Moreover, the logistic regression result in Table 3 reveals that only the *PosGreen* condition significantly increased green plan choice at the \$5 price premium. A similar pattern emerges for the *pro-gray* case, where the *PosGray* condition decreased green plan choice by 8.9 percentage points, while *NegGreen* decreased it by only 5.6 percentage points, although this difference is not significant ($p = .190$). However, the *PosGray* condition (and the *NegGreen+PosGray* condition) significantly reduced green plan choice relative to the *Baseline,* whereas the *NegGray* is not significant. At the low \$5 price premium for the green plan, positive information (especially about the green plan) seems to evoke a stronger response.

Overall, the data suggest that the cost of the green plan, relative to the gray plan, can be an important factor in determining the differential effectiveness of information nudges. When the voluntary green plan is not *too* expensive, highlighting the positive attributes of green electricity generation would be most effective in promoting its adoption. Conversely, if the green plan is relatively expensive, then highlighting the negative aspects of gray electricity generation seems to have more bite; perhaps appealing to some implicit degree of moral wrongdoing by choosing the "bad" gray plan is more effective in overcoming the relatively high price premium of the green plan. The

31. This difference is not significant using a Chi-squared test corrected for clustering ($p = .196$).

Figure 3: Impact of Information Conditions by Price Premium





other side of this story is that when the green plan is expensive, then information about the possible disadvantages of renewable electricity can really handicap its adoption; here, it seems people jump at the opportunity to justify not paying the premium for the green plan if the green plan is really "not all that good". From a practical perspective, the results suggest that optimal approach for marketing a voluntary green plan might be a function of the green price premium; hence, the content of marketing information be have to be tailored based on how competitively priced the green plan is.

Table 3: Logit Models with Green Plan Choice as Dependent Variable (by Price Premium)

	Dependent Variable: *Green Plan Choice*		
	$5 Price Premium	$10 Price Premium	$15 Price Premium
PosGreen	.112***	.084***	.042
	(.032)	(.030)	(.029)
NegGray	.048	.111***	.067**
	(.039)	(.037)	(.034)
PosGreen+NegGray	.046	.064*	.063*
	(.038)	(.035)	(.033)
NegGreen	–.038	–.060**	–.067**
	(.032)	(.031)	(.032)
PosGray	–.082**	–.040	.001
	(.037)	(.037)	(.036)
NegGreen+PosGray	–.111***	–.078**	–.037
	(.039)	(.037)	(.036)
Respondent Controls	Yes	Yes	Yes
Block Dummies	Yes	Yes	Yes
Respondent Clustering	Yes	Yes	Yes
N	7,096	7,064	7,098

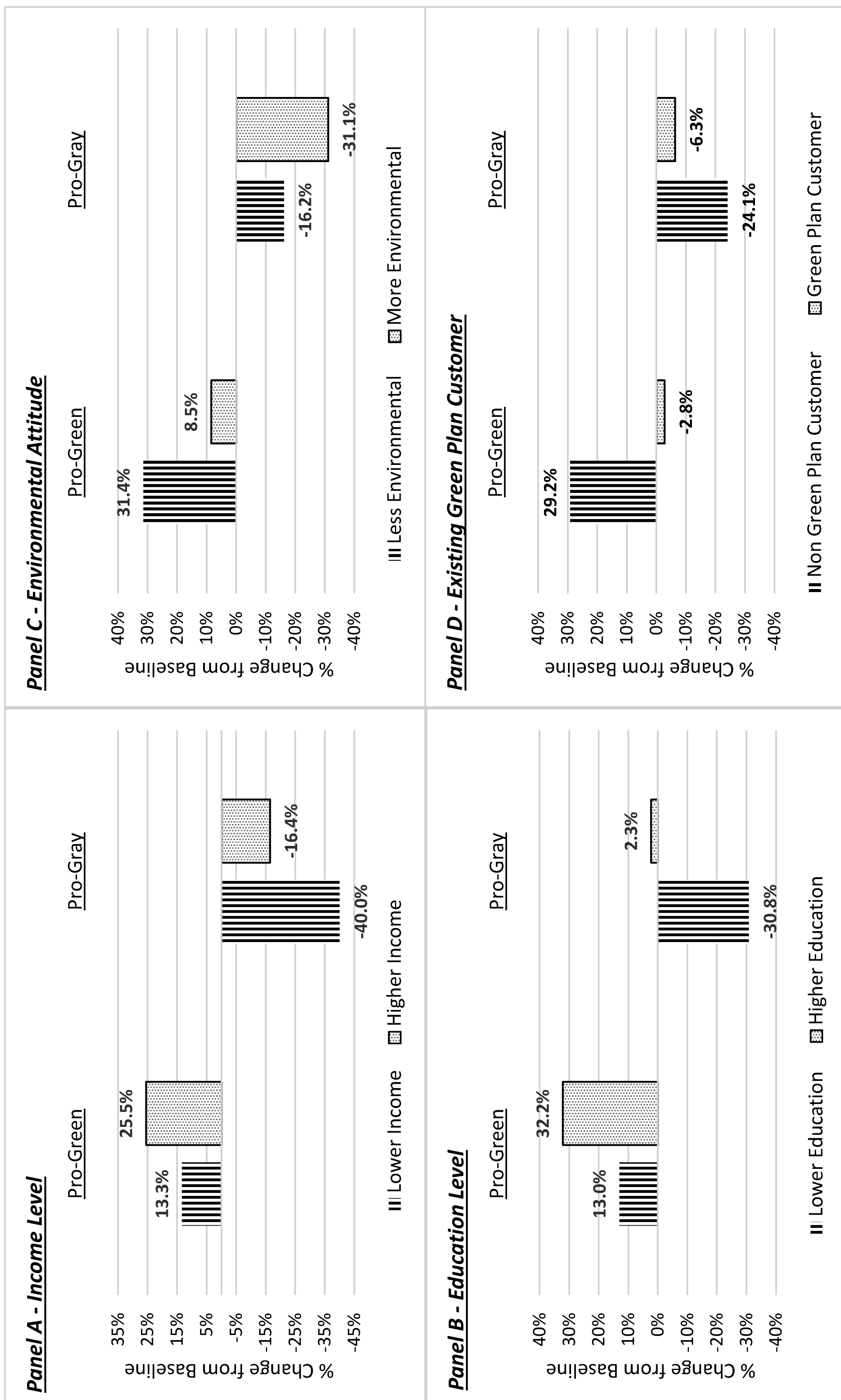
Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Marginal effects are reported with standard errors in parentheses. *** significance at 1% level; ** significance at 5% level; * significance at 10% level

4.4 Heterogeneous Responses to Treatment of Information by Respondent Characteristics

Table 2 shows some of the individual respondent characteristics significantly impacted the decision to choose the green plan. While this direct effect is certainly of interest, it is also important to think about how different "types" of respondents might differentially respond to information. Specifically, we consider how respondents' level of income, education, and general environmental attitude differentially impact their responses. For ease of interpretation, we stratify the data based on reported values of these characteristics, and then examine treatment effects categorically, relative to the corresponding *Baseline* rate of green plan selection. For both income and education, we classify respondents into two group: (i) *higher* if they are above the median, and (ii) *lower* if they are below the median. For environmental attitude, we also stratify respondents into two groups: (i) *more environmental* if their NEP score is above the median, and (ii) *less environmental* if their NEP score is below the median. Lastly, we also consider whether respondents are enrolled in an existing green plan at their current utility company. To streamline the presentation of the analysis, we aggregate over all information conditions within the given type of condition: *pro-green* or *pro-gray*. Moreover, for this sub-sample analysis, we use only the Qualtrics panel, where we have sufficient variation in respondent characteristics of interest for meaningful analysis. Figure 4 presents stratified data. Because the *Baseline* level of green plan choice differs based on how respondents are categorized (e.g., *more environmental* vs. *less environmental*), Figure 4 reports the *% change* in aggregate green plan choice, relative to the corresponding *Baseline* level. By reporting everything as a % change relative to baseline, we account for the fact that different groups might be more/less responsive to the information condition based on their baseline level of green plan selection. For robustness, we also perform additional sub-sample logit regressions and, analysis with interaction terms between treatment and respondent characteristics; the results are reported in Appendix D.

Looking first at respondent income, Panel A reveals some potential differences in how lower- and higher-income respondents are affected. Both income groups show a large positive response to the *pro-green* conditions and a large negative response to the *pro-gray* conditions. There is a significant main effect of information condition (ANOVA: $p < .001$), but the interaction be-

Figure 4: Impact of Information Conditions by Respondent Characteristics



tween information condition and income is not significant. The sub-sample analysis reported in Appendix D provides some marginal support for the idea that lower-income respondents are more responsive to the *pro-gray* conditions, while higher-income respondents may be more responsive to the *pro-gray* conditions, a pattern that appears to emerge in Panel A. Looking next at education level, Panel B reveals some differences in how more-educated respondents respond. Indeed, there is a significant main effect of education (ANOVA: $p < .001$), and interaction between education and information condition (ANOVA: $p < .001$). In particular, we see that more-educated respondents are relatively more likely to choose the green plan after receiving the *pro-green* information, while less-educated respondents are much less likely to choose the green plan after receiving the *pro-gray* information. Given the correlation between education and income, one possible way to interpret this is that less-educated/lower-income respondents are more *skeptical* or cautious regarding green-power; hence, they do not show as large of a positive response to pro-green nudges, and conversely, show a much larger negative response to the pro-gray nudges. Thus, one possible implication is that more-educated/higher-income customers might be relatively easier to convince to adopt a voluntary green plan through the provision of pro-green plan information.

Panel C compares how respondents with different environmental attitudes respond to the information. It is evident that measured environmental attitudes (*NEP*) differentially impact green plan choice; there is a significant main effect of *NEP* (ANOVA: $p < .001$), and interaction effect of NEP and information condition (ANOVA: $p < .001$). Specifically, less-pro-environmental respondents are more responsive to the *pro-green* information and show a larger increase in green plan selection. However, the opposite is true for the *pro-gray* information; more-pro-environmental respondents exhibit a stronger negative response to the *pro-gray* conditions. The intuition here is individuals who are more concerned about the environment are less likely to be influenced by pro-green information, as this likely just confirms their existing beliefs. At the same time, individuals with more concern for the environment are more responsive to pro-gray information; if the gray plan is “not that bad” or the green plan is “not that good”, the more-pro-environmental respondents exhibit a larger decrease in green plan selection. This could be consistent with a moral licensing story (Blanken et al., 2015), where more-pro-environmental respondents use the pro-gray information as justification to “license” their pro-gray choice.

Lastly, Panel D of Figure 4 compares the behavior of existing green plan customers versus non-existing green plan customers. Importantly, we see a significant difference in how these two groups react to the information intervention (ANOVA: $p < .001$). As we would expect, existing green plan customers are much less responsive to both the *pro-green* and *pro-gray* information interventions, in that neither appear to impact the green plan selection rates. Conversely, the non-existing green plan customers show a large positive response to the *pro-green* conditions and a large negative response to the *pro-gray* conditions. The main implication here is that individuals who are not existing green plan customers are much more “nudge-able” in that their behavior is more influenced by the pre-choice, information intervention. This is comforting from a green-power marketing perspective in that we would want pro-green information to have the largest impact on green plan adoption for new customers. Moreover, our data also suggests some “sticking power” of green plan adoption in that existing green plan customers are more difficult to nudge away from the green plan.

4.5 Persistence of Information Manipulation

Recall, respondents faced a series of 12 plan choice scenarios after having been treated with the information manipulation. A benefit of this design feature is our ability to examine the *persistence* of the information manipulation over the plan choices. To do so, we reproduce our main logit specifications reported in Table 2 with the addition of interaction terms between each of the six information conditions and the choice number—*choice#*—which takes value from 1 to 12. Because the dependent variable takes the value one when the green plan is chosen, a negative, significant interaction of *choice#* with the three *pro-green* conditions (*PosGreen, NegGray,* and *PosGreen+NegGray*) would indicate a "wear off" effect, while a positive, significant interaction of *choice#* with the three *pro-gray* conditions (*PosGray, NegGreen,* and *PosGray+NegGreen*) would indicate a "wear off" effect. Table 4 presents the results.

We see a striking pattern emerge in comparing the persistence of the *pro-green* and *pro-gray* information conditions. Specifically, when looking at Table 4, we see that the interaction terms of the three *pro-green* conditions with the *choice#* are never statistically significant across all four reported specifications. However, when looking at the interactions of the three *pro-gray* conditions with the *choice#,* all but one of the twelve reported interactions are positive and statistically significant. Thus, the data reveal no significant wear off of the *pro-green* information as the respondents

Table 4: Persistence of Information Conditions on green plan choice

	Dependent Variable: *Green Plan Choice*			
	1	2	3	4
PosGreen	.297**	.336**	.299**	.334**
	(.143)	(.141)	(.144)	(.141)
NegGray	.311*	.276*	.312*	.268
	(.164)	(.170)	(.167)	(.173)
PosGreen+NegGray	.157	.157	.162	.158
	(.159)	(.162)	(.161)	(.164)
NegGreen	–.487***	–.416***	–.506***	–.437***
	(.144)	(.144)	(.146)	(.145)
PosGray	–.323*	–.319*	–.339*	–.346**
	(.171)	(.172)	(.174)	(.174)
NegGreen+PosGray	–.518***	–.527***	–.530***	–.551***
	(.168)	(.170)	(.170)	(.172)
$10 Price Premium			–.484***	–.509***
			(.030)	(.031)
$15 Price Premium			–1.065***	–1.111***
			(.041)	(.044)
PosGreen ***X*** *Choice#*	.003	.002	.005	.005
	(.012)	(.013)	(.012)	(.012)
NegGray ***X*** *Choice#*	.013	.011	.015	.015
	(.013)	(.014)	(.013)	(.014)
PosGreen+NegGray ***X*** *Choice#*	.018	.017	.019	.019
	(.013)	(.013)	(.012)	(.013)
NegGreen ***X*** *Choice#*	.029**	.028**	.030**	.029**
	(.013)	(.014)	(.013)	(.013)
PosGray ***X*** *Choice#*	.022*	.021	.024*	.025*
	(.014)	(.014)	(.014)	(.014)
NegGreen+PosGray ***X*** *Choice#*	.029**	.028**	.029**	.030**
	(.012)	(.013)	(.012)	(.013)
Choice#	–.032***	–.032***	–.009	–.008
	(.009)	(.009)	(.008)	(.009)
Respondent Controls	No	Yes	No	Yes
Block Dummies	Yes	Yes	Yes	Yes
Respondent Clustering	Yes	Yes	Yes	Yes
N	21,384	21,258	21,384	21,258

Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Estimated Coefficients are reported with standard errors in parentheses. The set of Respondent Controls (when included) are the same as those reported in Table 2.
*** significance at 1% level; ** significance at 5% level; * significance at 10% level

progress through the choice sets, but there does appear to be a wear off of the *pro-gray* information manipulations.

To portray these results more clearly, Table 5 reports the estimated marginal effects of the six information conditions from the full specification reported in Column 4 of Table 4, evaluated at *choice#* = 1 (the first choice) and *choice#* = 12 (the last choice). A striking difference in the persistence of the manipulation between the *pro-green* and *pro-gray* conditions is evident. Specifically, at *choice#* = 12, the marginal effects for the three *pro-green* conditions are all positive and significant (ranging from 8.3 to 9.8 percentage points). Whereas the marginal effects for the three *pro-gray* conditions are negative and significant when evaluated at *choice#* = 1, but are all insignificant when evaluated at *choice#* = 12. This suggests that by choice set #12, there is no longer a significant effect of having received *pro-gray* information on the likelihood of choosing the green plan. On the other hand, those respondents who received *pro-green* information are about 9 percentage points more likely to choose the green plan in their last choice. In our view this is an encouraging finding, assuming the goal would be to promote the adoption of these voluntary green plans; namely, it suggests it might be less important *when* this information is presented, but rather that it is provided *at some point* prior to making their plan decision.

Table 5: Marginal Effects of Information Conditions at Choice# = 1 and Choice# = 12

		Estimated Marginal Effects Evaluated at:	
	Information Condition	*Choice#* = 1	*Choice#* = 12
Pro-Green	*PosGreen*	.073***	.087***
		(.029)	(.030)
	NegGray	.060*	.098**
		(.036)	(.038)
	PosGreen+NegGray	.037	.083**
		(.034)	(.037)
Pro-Gray	*NegGreen*	–.082***	–.018
		(.026)	(.029)
	PosGray	–.065**	–.011
		(.032)	(.036)
	NegGreen+PosGray	–.103***	–.041
		(.030)	(.035)
	$10 Price Premium	–.106***	–.109***
		(.006)	(.006)
	$15 Price Premium	–.231***	–.239***
		(.008)	(.009)

Notes: This table reports the estimated marginal effects of the logit regression reported in Column 4 of Table 4 with green plan choice as the binary dependent variable. Columns 1 and 2 report the estimated marginal effects evaluated at choice# = 1 and choice# = 12, respectively. Standard errors in parentheses.
*** significance at 1% level; ** significance at 5% level; * significance at 10% level

5. DISCUSSION AND CONCLUSIONS

There is a global concerted effort, especially from regulating bodies, to promote growth in renewable energy as a means to combat global warming, curb greenhouse gas emissions, and facilitate sustainability. Moreover, residential electricity usage accounts for a sizable share of overall energy demand.[32] As such, deepening our understanding of the possible factors that can influence consumers' attitudes and choices to adopt voluntary green-power plans is critically important to the

32. For example, in 2019 the EIA reported (https://www.eia.gov/outlooks/aeo/pdf/AEO2020%20Full%20Report.pdf) that electric power generation accounted for roughly 38% of total U.S. energy consumption, and that the residential sector accounted for over 1/3 of total electricity use.

progression of renewable energy and the evolution of energy production and consumption. The aim of this study is to contribute to this understanding by examining how non-price, information nudges impact consumers' preferences for selecting voluntary green-power plans.

In particular, we carry out a choice experiment where respondents choose between a conventional *gray-power plan* and a renewable *green-power plan*. Prior to making their stated plan selections, respondents are randomly exposed to a: (i) pro-green nudge—receiving information about the advantages of green power and/or the disadvantages of gray power, or (ii) pro-gray nudge—receiving information about the disadvantages of green power and/or the advantages of gray power. Importantly, we also vary the green-price premium across choice sets. Consequently, we are able to identify how these information interventions impact selection rates of the green plan relative to a *baseline* rate of selection, and compare the magnitude of the effects to the magnitude of the price premium effect.

We document economically and statistically significant effects of the information interventions on selection rates of the green plan. Notably, the *pro-green* information nudges increase green plan choice by 6–8 percentage points, relative to the 36% baseline rate of selection. Conversely, the *pro-gray* information nudges decrease green plan choice by 5–8 percentage points relative to the baseline. Based on our estimates, the magnitude of the information nudges are roughly proportional to a change in the green plan price premium of roughly $4 per month. Moreover, our results are generally robust across different levels of price premium for the green plan.

Interestingly, the estimated increase in green plan selection after being exposed to the *pro-green* information intervention is persistent and remains statistically significant throughout the entire set of choices. Whereas, we see a significant "wear off" of being exposed to the *pro-gray* information intervention; based on our estimates, by the time respondents have progressed to their last choice (i.e., the choice furthest removed from the time they viewed the information), there is no longer a significant effect of having received the *pro-gray* information on choosing the green plan. We acknowledge that the idea of persistence within our experimental framework needs to be interpreted with some caution (given the short elapsed time). That said, the fact that we see a striking difference in persistence between the pro-green and pro-gray information provides some suggestive evidence of the staying-power of pro-green information nudges on the decision to adopt voluntary green power plans.

Given the hypothetical nature of the stated-preference choice experiment, it is possible that there is some bias and/or experimenter demand effects, presumably in the direction of higher levels of stated green plan selection; this can lead to disparities between stated preferences and actual green plan adoption (see Diaz-Rainey & Tzvara, 2012 for a discussion). Thus, some caution needs to be taken when interpreting treatment effects associated with the information nudges. Importantly, however, we identify our main information treatment effects relative to a *baseline* level of green plan selection. Therefore, if we make the reasonable assumption that any green bias (if it exists) is uncorrelated with the information interventions, our estimated treatment effects *relative* to the baseline remain valid. Moreover, by varying price premium of the green plan, we can estimate a price effect and, thus, interpret the magnitude of the information effects *relative* to the price effect. As such, even if the absolute size of the information effects are possibly inflated, our results suggest that information nudges can impact green plan adoption by a similar magnitude to reasonably sized changes in the monthly green price premium. That said, we view this study as an important initial step in signaling the potential effectiveness for information nudges to increase the take-up of voluntary green electricity plans to better match legislative enthusiasm for green energy developments. Naturally, a large-scale field experiment would be an important follow-up to buttress the findings in this study.

Our study can be informative for renewable energy policy. Sustaining continued growth in renewable energy hinges on continued increases in consumer demand for green products. Among these, increasing the demand for residential, green electric power can be impactful for increasing overall renewable energy as a share of total energy production. Our results suggest that policies aimed at providing more salient information about the environmental and social benefits of green-power generation, or the costs of gray-power generation, could increase adoption of voluntary green-power plans, thus stimulating overall growth in the renewable energy sector. An example would be to mandate that electric utilities provide (transparent) information disclosures of energy generating sources and the associated environmental impacts. In essence, mandating a type of "eco-labeling" for electric utility plans could increase take-up of green-power plans in the same way eco-labeling has promoted adoption of more energy-efficient durable goods.[33] Moreover, promoting residential adoption of green-power plans through such information nudging might be preferred to conventional economic polices (e.g., subsidies, tax breaks, mandates) since nudges have the (desirable) property of being libertarian or choice-preserving, while also possibly aligning choices more in the direction of people's preferences for more renewable energy; hence, falling under the category of being libertarian paternalistic (Thaler & Sunstein, 2008).

The results from our study also have important green-power marketing implications. Namely, providing information about the beneficial attributes associated with renewable electricity generation is a plausible mechanism that electric utilities could use to increase the take-up rate of voluntary green plans; this could be especially useful as utility companies are being tasked with complying with government mandates stipulating increasing the share of renewable energy. Dagher et al. (2017) find that take-up of green plans is lower for new subscribers compared to existing customers. The findings from our study suggest that when marketing to new customers, utilities can "nudge" new customers to adopt the green plan by providing salient information about the benefits of the green plan. Relatedly, such information would be more effective if utilities target people who might be relatively less environmentally conscious. Alternatively, this could also cut the other way with utility companies being able to discourage customers from switching to an alternative green plan through pro-gray nudges. Regardless, our study suggests that this type of pre-plan-selection, information provision can be a useful strategy for electric utilities to steer new customers toward certain plans. Naturally, as renewable electricity generation becomes cheaper, via increasing efficiency from advancements in renewable energy technologies, this strategy would imply steering customers toward green plans.

Overall, we view our study as contributing to and extending the extant literature aimed at identifying the possible factors that influence consumers' decisions to adopt green-power plans. Much of this prior literature has focused on price of the green plan or other conventional economic levers; namely, lowering the price of the green plan or raising the incentive to adopt the green plan. While prices and incentives are important determinants, they alone deliver an incomplete view. Our results suggest that non-price interventions can also play an important role. Specifically, *nudging* people by providing (pre-choice) information about the advantageous or disadvantageous attributes of electricity generation associated with green and gray plans can significantly impact demand for voluntary green-power plans. From a descriptive perspective, our results can be informative for

33. As a referee aptly noted, a potentially important caveat is there might be differences in the salience of labeling between appliances and energy plans. Namely, eco-labeling (e.g. Energy Star) for appliances is very visible so everyone is essentially consuming that information. However, not all utility customers are likely to read the detailed plan information; hence, the effect of "eco-labeling" on utility plans might not be as large. Also, this further highlights the importance of certifying such voluntary green plans (e.g., Green-e certification) as discussed by Dagher et al. (2017).

better understanding the possible factors that can impact growth of renewable energy and the overall electricity generation moving forward.

Viewed through a broad lens, non-price nudges have been lauded by many academics, practitioners, and policymakers as effective instruments in promoting energy conservation (e.g., usage feedback, peer comparisons, social norms, and moral suasion). That said, recent work by Allcott & Kessler (2019) and Allcott & Greenstone (2017) suggests that there can be *indirect* costs associated with nudging conservation that are incurred when people change their behavior, which are typically not accounted for in welfare analysis. However, we argue that when it comes to electric power-plan choice, there are likely to be small (and possibly zero) indirect costs associated with choosing a green plan (because condition on the cost, once they choose the plan, their actual usage behavior is *presumably* not impacted by how the energy is being generated). We conclude by positing that nudging the usage-preceeding decision of consumers to adopt voluntary green-power plans might be a more attractive means for promoting the broader pro-environmental/sustainability energy agenda. Thus, from a welfare perspective, if we want to reduce greenhouse gas emissions and make improvements on climate change, we might be better served by focusing on using nudges to motivate people to adopt voluntary green-power plans. Overall, our study provides valuable insights regarding possible changes in energy consumption patterns in response to both regulatory changes and green power marketing aimed at promoting the adoption of green power.

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APPENDIX A: EXPERIMENTAL PROTOCOL

Upon opening the survey, participants were first consented to participate in the study by reading through a brief information sheet and then voluntarily agreeing to participate by clicking to continue to the survey. Participants were then provided with a general overview of the survey that read as follows:

Overview of the Survey

This survey will have several parts. The first part of the survey involves making decisions about which electricity plan you would choose from the options provided by a local electric utility. You will be presented with several hypothetical choice scenarios, and in all of the scenarios presented to you, there will always be two plan options offered by the electric utility: Plan A and Plan B.

Plan A electricity is the conventional alternative and is generated by combustion of coal or natural gas. Plan B electricity is the green alternative and is generated by a renewable source like wind or solar. In addition to how the electricity is generated between the two plan options in each scenario, there will also be potential differences in the average monthly cost between the two plans. In each scenario, you will be provided with information about the monthly price of each plan for a typical usage level.

If you are currently a customer of an electric utility company, then imagine each scenario as representing a setting where your utility company contacts you and presents you with information on two new plans and you must choose one of the plans. If you are not currently a utility customer, then imagine each scenario as representing a setting where you contact the utility about starting up service and they present you with information on two plans and you must choose one of the plans.

When making your decision about the plan you would choose in each scenario, please make your selection under the condition that you would be committed to that plan for a period of at least 12 months. All of the pricing information provided will be in terms of a projected monthly price associated with the usage of a typical consumer. For each scenario, please imagine that you are a typical consumer. We kindly ask that you carefully consider all the information provided to you, you seriously consider the options available, and you answer honestly about which electricity plan you would choose based on the information provided. In the survey you will be asked to make a plan choice for 12 different scenarios

After reading through the general overview, Participants were provided with a brief description of a sample choice scenario, and asked to answer four comprehension check questions. They were required to ultimately answer the questions correctly before proceeding. Below is copy of the specific information Participants received:

Sample Choice Scenario

For each of the choice scenarios, you will be provided with an information table for both of the electricity plans offered in that scenario. For each plan, the table will reveal how the electricity is generated (either conventional or green) and monthly pricing information for the plan.

Because the cost of generating electricity is variable, the rates that the utility company charges for each plan are subject to change. For each of the two plans offered, the table will provide information on the possible price volatility associated with each plan. Specifically, the table will display information on the possible monthly prices, and the likelihood of that price occurring (displayed as a percentage). The average expected monthly price of each plan will also be displayed at the bottom of the table.

Below is a sample of the information you will be given for each decision scenario you will encounter:

PLAN A – CONVENTIONAL ELECTRICITY	
Generating Source: Coal or Natural Gas	
Possible Monthly Price	**Chance of Price**
$93	15%
$100	70%
$107	15%
Average Expected Monthly Price: $100	

PLAN B – GREEN ELECTRICITY	
Generating Source: Wind or Solar	
Possible Monthly Price	**Chance of Price**
$98	10%
$108	80%
$118	10%
Average Expected Monthly Price: $108	

Based on the scenario presented above, for Plan A (the conventional electricity plan) there would be a 70% chance your monthly bill would be $100, a 15% chance the bill would be $93, and a 15% chance the bill would be $107. On average, you would expect to pay $100/month under Plan A.

Alternatively, for Plan B (the green electricity plan) there would be an 80% chance your monthly bill would be $108, a 10% chance the bill would be $98, and a 10% chance the bill would be $118. On average, you would expect to pay $108/month under Plan B.

Please answer the following questions about the above example scenario:

1) What is the average expected monthly price of electricity under Plan A
2) What is the average expected monthly price of electricity under Plan B
3) What is the highest possible monthly price of electricity under Plan A
4) What is the % chance of having to pay $118 in a month for electricity under Plan B

Participants were then randomly assigned to treatment, provided with the corresponding information intervention (detailed in Appendix B), and asked to make their plan selection in each of the 12 choice scenarios. Lastly, they were asked to fill out the short demographic survey.

APPENDIX B: COPY OF INFORMATION STATEMENTS

Panel A—Information about Conventional Gray Electricity Generation	
Advantages	**Disadvantages**
● There is an abundance of coal and natural gas ● The electricity that is generated is continuous during peak times ● It is a relatively cheap and reliable energy source ● It is versatile and can be used in a variety of applications and different environments ● It is easy to store and transport coal and natural gas to electricity-generating facilities ● Modern coal and natural gas power plants are very energy efficient	● Are nonrenewable sources of energy that deplete over time ● Emits greenhouse gases into the atmosphere ● Emits harmful substances like sulfur dioxide, which can lead to acid rain ● Environmental damage is associated with mining coal and obtaining natural gas ● Mining coal is dangerous and hazardous to the health of miners ● Over 500 gallons of fresh water are used per megawatt hour of electricity generated
Panel B—Information about Renewable Green Electricity Generation	
Advantages	**Disadvantages**
● No limit to the energy sources in the future ● Doesn’t contribute to greenhouse gas emissions ● Doesn’t produce air pollution that can be harmful to humans ● It is a domestic source of energy, reducing our nation’s dependence on trade ● It is beneficial to rural economies ● Doesn’t use freshwater resources	● It doesn’t provide a continuous source of electricity (sun doesn’t always shine and the wind doesn’t always blow) ● Requires large areas of land to be disrupted, potentially damaging ecosystems ● Often developed long distances from where the electricity is needed, requiring the construction of transmission lines ● Difficult to store and transport the energy ● Expensive relative to conventional sources ● Pollution and emissions are generated during the manufacturing process
Panel C—Information about Electricity Generation	
Neutral	
● According to the U.S. Energy Information Administration, the average U.S. household used 11,000 KWh of electricity in 2014 ● Space cooling and lighting account for about 25% of the total U.S. residential electricity use ● There are more than 450,000 miles of high-voltage transmission lines in the U.S to move electricity from the generating source to the end user ● The U.S. EIA estimates that in 2013, 5% of generated electricity was lost in transmission and distribution ● The average price for electricity in the U.S. is $0.12 per KWh ● The price of electricity varies throughout the day and throughout the year	

APPENDIX C: INFORMATION INTERVENTION MANIPULATION CHECK

As part of the experimental design, respondents were provided with information about either: (i) positive or negative information about the gray plan, (ii) positive or negative information about the green plan, (iii) some combination of positive or negative information about both plans, or (iv) neutral information (generic facts about electricity). This information intervention was in the form of a block of six statements pertaining to attributes associated with the electricity generated from the given source. Our aim was to provide information that highlighted either the possible advantages or disadvantages of electricity generation associated with renewable green power generation or conventional gray power generation. The specific statements that were used for each manipulation are presented above in Appendix B. To verify that the collection of statements in each condition incited the desired perception about the corresponding plan, we tested the manipulation on an independent sample (n = 136) of participants drawn from the same business school student population who completed the choice-based experiment (although no respondents participated in both tasks).

We implemented the following survey procedure. All participants were shown the collection of six neutral statements about electricity facts that comprised the *Baseline* condition. There were then instructed to think about whether the statement is supportive of: (i) conventional, hydro-carbon electricity generation (e.g., coal or natural gas), (ii) renewable, green electricity generation (e.g., wind or solar), or (iii) neutral, and then indicate their response on the Likert scale from 1 to 7 provided (1=supporting hydro-carbon electricity; 4=neutral; 7=supporting green electricity). In addition, participants were also shown either all twelve statements pertaining to the green plan (six from *PosGreen* and six from *NegGreen*) or all twelve statement pertaining to the gray plan (six from *PosGray* and six from *NegGray*). They were then instructed to indicated on a Likert scale from 1 to 7 whether each statement was positive or negative (1=very negative; 7=very positive).

Several measures were implemented to minimize order affects. First, we randomized whether respondents rated the six neutral statements first or the twelve gray/green plan statements first. Second, we randomized the order of the twelve gray/green plan statements such that advantageous and disadvantageous statements were mixed together. Third, we considered four different blocks (each with a different order of the statements) and tested for block effect (which we didn't find any significant effects). The average scaled evaluation of each statement, as well as the overall, respondent-level average across all six statements is provided in the tables below:

Evaluation of Neutral Information Statements (N= 136)

Statement	Average Ranking 1=ProGray; 7=ProGreen 4=Neutral
[1] According to the U.S. Energy Information Administration, the average U.S. household used 11,000 KWh of electricity in 2014	3.44
[2] Space cooling and lighting account for about 25% of the total U.S. residential electricity use	3.85
[3] There are more than 450,000 miles of high-voltage transmission lines in the U.S to move electricity from the generating source to the end user	3.49
[4] The U.S. EIA estimates that in 2013, 5% of generated electricity was lost in transmission and distribution	3.51
[5] The average price for electricity in the U.S. is $0.12 per KWh	3.60
[6] The price of electricity varies throughout the day and throughout the year	3.92
Overall Respondent-level average over all six items	3.63

Evaluation of Gray Plan Statements (N=79)

Statements	Average Ranking 1=Negative; 7=Positive 4=Neutral
Advantages (PosGray condition) 1) There is an abundance of coal and natural gas	5.20
2) The electricity that is generated is continuous during peak times	4.82
3) It is a relatively cheap and reliable energy source	5.82
4) It is versatile and can be used in a variety of applications and different environments	5.63
5) It is easy to store and transport coal and natural gas to electricity-generating facilities	5.30
6) Modern coal and natural gas power plants are very energy efficient	5.61
Overall Respondent-level average over all six *PosGray* items	5.41
Disadvantages (NegGray condition) 7) It is derived from nonrenewable sources of energy that deplete over time	2.52
8) It emits greenhouse gases into the atmosphere	2.35
9) It emits harmful substances like sulfur dioxide, which can lead to acid rain	1.85
10) Environmental damage is associated with mining coal and obtaining natural gas	2.42
11) Mining coal is dangerous and hazardous to the health of miners	1.97
12) Over 500 gallons of fresh water are used per megawatt hour of electricity generated	2.86
Overall Respondent-level average over all six *NegGray* items	2.33

Evaluation of Green Plan Statements (N=57)

Statements	Average Ranking 1=Negative; 7=Positive 4=Neutral
Advantages (PosGreen condition) 1) No limit to the energy sources in the future	5.93
2) Doesn't contribute to greenhouse gas emissions	5.81
3) Doesn't produce air pollution that can be harmful to humans	6.14
4) It is a domestic source of energy, reducing our nation's dependence on trade	5.58
5) It is beneficial to rural economies	5.77
6) Doesn't use freshwater resources	5.00
Overall Respondent-level average over all six *PosGreen* items	5.70
Disadvantages (NegGreen condition) 7) It doesn't provide a continuous source of electricity (sun doesn't always shine and the wind doesn't always blow)	3.16
8) It requires large areas of land to be disrupted, potentially damaging ecosystems	2.16
9) The electricity is often generated long distances from where the electricity is needed, requiring the construction of transmission lines	3.47
10) It is difficult to store and transport the energy	3.12
11) It is expensive relative to conventional sources	3.14
12) Pollution and emissions are generated during the manufacturing process	2.35
Overall Respondent-level average over all six *NegGreen* items	2.90

APPENDIX D: ADDITIONAL DATA ANALYSIS

Data from Ambiguous Conditions

For brevity, in the main text we do not report any analysis from the two ambiguous conditions—*PosGreen+PosGray* and *NegGreen+NegGray*—which were included as part of the full factorial design. In footnote 23 we discuss how these two conditions yield largely null findings in terms of their impact on planned adoption of the green plan, as we might expect given their (ex-ante) ambiguous nature. Below we reproduce the aggregate data from these conditions in Figure 2.A1, as well as the main regression analysis in Table 2.A1. As can be verified from Table 2.A1, the two ambiguous conditions result in a largely null effects on their impact of green plan selection.

Figure 2.A1: Impact of Information Conditions on Adoption of Green-power Plan (Including *Ambiguous* conditions)

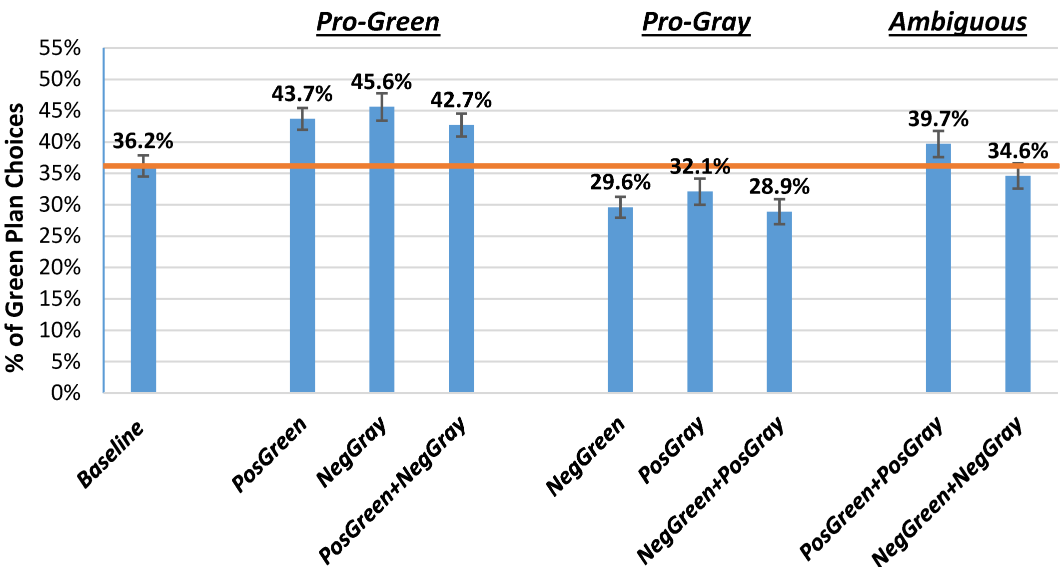


Table 2.A1: Logit Models with Green Plan Choice as Dependent Variable (Including Ambiguous Conditions)

	Dependent Variable: *Green Plan Choice*			
	1	2	3	4
PosGreen	.073***	.078***	.073***	.078***
	(.027)	(.025)	(.027)	(.025)
NegGray	.092***	.076**	.092***	.076**
	(.033)	(.032)	(.033)	(.032)
PosGreen+NegGray	.065**	.058*	.065**	.058*
	(.032)	(.031)	(.032)	(.031)
NegGreen	–.069***	–.052**	–.069***	–.052**
	(.026)	(.025)	(.026)	(.025)
PosGray	–.039	–.040	–.039	–.040
	(.034)	(.032)	(.034)	(.032)
NegGreen+PosGray	–.074**	–.077**	–.074**	–.077**
	(.034)	(.032)	(.034)	(.032)
PosGreen+PosGray	**.037**	**.033**	**.037**	**.033**
	(.032)	**(.031)**	**(.032)**	**(.031)**
NegGreen+NegGray	**–.012**	**–.012**	**–.013**	**–.012**
	(.032)	(.031)	(.032)	(.031)
$10 Price Premium			–.109***	–.109***
			(.006)	(.006)
$15 Price Premium			–.231***	–.231***
			(.008)	(.008)
Male		–.013		–.013
		(.016)		(.016)
Education		.016***		.016***
		(.006)		(.006)
Income		.005		.005
		(.004)		(.005)
Children		–.045**		–.045**
		(.022)		(.022)
Green Plan Customer		.050**		.050**
		(.025)		(.025)
NEP Scale		.002**		.002**
		(.001)		(.001)
Green Electricity		.080***		.080***
		(.010)		(.009)
RSRP	.008	–.007	.008	–.006
	(.016)	(.020)	(.016)	(.020)
Block Dummies	Yes	Yes	Yes	Yes
Respondent Clustering	Yes	Yes	Yes	Yes
N	21,384	21,258	21,384	21,258

Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Marginal effects are reported with standard errors in parentheses. *** denotes statistical significance at the 1% level; ** denotes significance at the 5% level.

Replication Main Analysis of Treatment Effects from the Qualtrics Panel Sample Only

In the main text we report results from the pooled sample of the representative Qualtrics Panel and the student sample. To ensure that our main results are robust, we replicate the main regression analysis reported in Table 2 for just the Qualtrics Panel only. Table 2.A2 reports the results, which are largely consistent with those reported in Table 2.

Table 2.A2: Logit Models with Green Plan Choice as Dependent Variable (Qualtrics Panel Only)

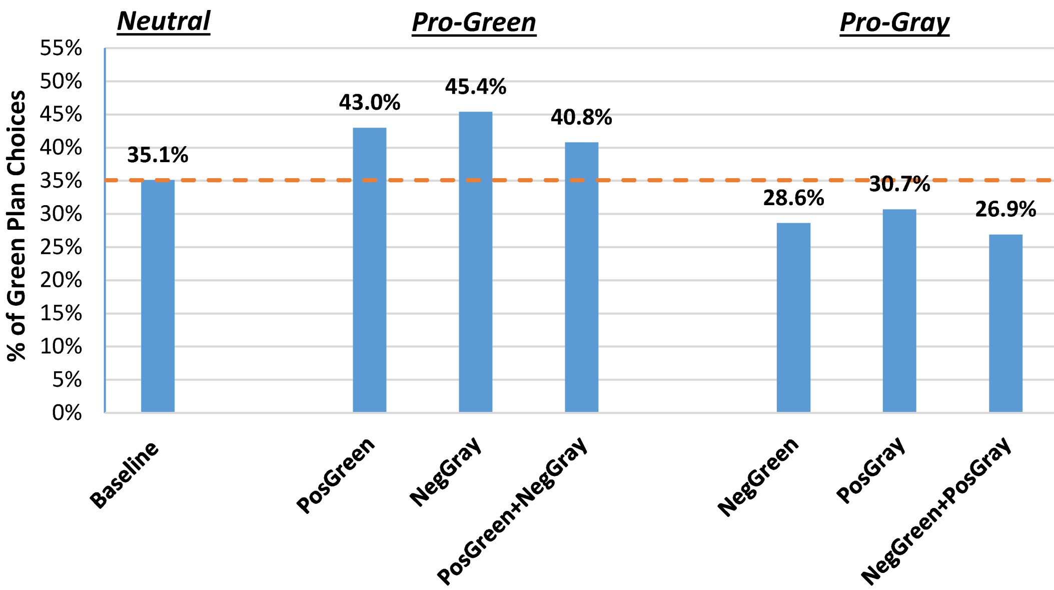
	Dependent Variable: *Green Plan Choice*			
	1	2	3	4
PosGreen	.095**	.102***	.096**	.102***
	(.042)	(.038)	(.042)	(.039)
NegGray	.087**	.075*	.087**	.075*
	(.044)	(.044)	(.044)	(.044)
PosGreen+NegGray	.060	.055	.060	.055
	(.043)	(.042)	(.044)	(.042)
NegGreen	–.127***	–.117***	–.127***	–.117***
	(.044)	(.042)	(.044)	(.042)
PosGray	–.037	–.033	–.037	–.033
	(.047)	(.044)	(.047)	(.044)
NegGreen+PosGray	–.070	–.066	–.070	–.066
	(.047)	(.044)	(.047)	(.044)
$10 Price Premium			–.087***	–.087***
			(.008)	(.008)
$15 Price Premium			–.179***	–.178***
			(.010)	(.010)
Male		–.008		–.009
		(.023)		(.023)
Education		.015**		.015*
		(.008)		(.008)
Income		.011		.011
		(.008)		(.008)
Children		–.065***		–.065***
		(.022)		(.022)
Green Plan Customer		.062**		.062**
		(.027)		(.027)
NEP Scale		.001		.001
		(.001)		(.001)
Green Electricity		.076***		.076***
		(.013)		(.013)
Block Dummies	Yes	Yes	Yes	Yes
Respondent Clustering	Yes	Yes	Yes	Yes
N	13,298	13,208	13,298	13,208

Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Marginal effects are reported with standard errors in parentheses. Only the Qualtrics panel sample is included.
*** significance at 1% level; ** significance at 5% level; * significance at 10% level

Exclusion of Those Participants who Reported that Their Current Utility Uses Green Energy

To ensure that our main results are not being bias by respondents who may have previously received information about green plans from their current utility provider, we reproduce the main treatment effects reported in Figure 2 *excluding* all respondents who self-reported that their current utility plan uses green energy. From Figure 2.A2 below, we see the result are generally consistent for this subsample.

Figure 2.A2: Impact of Information Conditions on Adoption of Green-power Plan (*excluding respondents where current utility used green energy)*



Additional Analysis of Heterogeneous Treatment Effects (Qualtrics Panel Only)

Here we provide additional analysis regarding the possible heterogeneous treatment effects based on observable respondent demographics. In Table 3.A we perform subsample analysis. For Income Level, Education, and Environmental attitudes we split the sample at the median. We then exclude those respondents at the median. We then classify respondents as being relatively *low/high* income and education if they are strictly below/above the reported median level. Similarly we classify respondents as being relatively *less/more* environmentally conscious if they are strictly below/above the median reported NEP level. Lastly, we categorize existing green plan customers as those who self-reported that they participate in a green plan. We re-run our main specification for each subsample separately.

In Table 4.A we run additional logit specifications with our measure of environmental attitude (*NEP* scale) and a dummy for existing *Green Plan Customer* interacted with our categorical treatment dummies—*pro-green* and *pro-gray.* We then report the marginal effects of these two treatment dummies on green plan selection evaluated when *NEP* = 25$^{\text{th}}$ percentile (*Less* environmental) and *NEP* = 75$^{\text{th}}$ percentile (*More* environmental); as well as when *Green Plan Customer* = 0 (*No*) and *green plan customer* = 1 (*Yes*).

Table 4.A: Interaction Effects of Treatment with Environmental Attitude and Green Plan Customer

	Dependent Variable: ***Green Plan Choice***					
	Environmental Attitude			Existing Green Plan Customer		
		Marginal Effects			Marginal Effects	
		Less	More		No	Yes
Pro-Green	1.63*	.101**	.040	.460**	.102**	–.065
	(.969)	(.040)	(.048)	(.182)	(.041)	(.081)
Pro-Gray	1.19	–.047	–.122***	–.406**	–.087**	–.067
	(.987)	(.041)	(.045)	(.191)	(.040)	(.080)
$10 Price Premium	–.396***			–.398***		
	(.036)			(.036)		
$15 Price Premium	–.813***			–.816***		
	(.049)			(.049)		
Pro-Green X NEP	–.026					
	(.019)					
Pro-Gray X NEP	–.031					
	(.019)					
Pro-Green X Green Plan Customer				–.739*		
				(.398)		
Pro-Gray X Green Plan Customer				.116		
				(.398)		
Respondent Controls	Yes			Yes		
Block Dummies	Yes			Yes		
Respondent Clustering	Yes			Yes		
N	13,208			13,208		

Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Only the Qualtrics panel sample is included. Colum 1 reports the estimated coefficients (with standard errors in parenthesis) when *NEP* scale is interacted with treatment. Columns 2 and 3 report the marginal effects evaluated at *NEP* = 25th percentile and *NEP* = 75th percentile, respectively. Column 4 reports the estimated coefficients (with standard errors in parenthesis) when *Green Plan Customer* is interacted with treatment. Columns 5 and 6 report the estimated marginal effects when *Green Plan Customer = 0 and Green Plan Customer = 1,* respectively.

*** significance at 1% level; ** significance at 5% level; * significance at 10% level

Table 3.A: Sub-sample Analysis: Estimated Logit Model with Green Plan Choice as Dependent Variable (Above/Below Median)

	Dependent Variable: *Green Plan Choice*							
	Income Level		Education Level		Environmental Attitude		Existing Green Plan Customer	
	Low	*High*	*Low*	*High*	*Less*	*More*	*No*	*Yes*
Pro-Green	.073	.085*	.025	.090	.099**	.029	.100***	.015
	(.074)	(.052)	(.054)	(.055)	(.046)	(.057)	(.038)	(.082)
Pro-Gray	–.127*	–.084	–.137**	–.025	–.046	–.139**	–.088**	–.035
	(.075)	(.054)	(.056)	(.060)	(.049)	(.057)	(.041)	(.082)
$10 Price Premium	–.093***	–.077***	–.101***	–.060***	–.082***	–.090***	–.094***	–.049**
	(.014)	(.014)	(.011)	(.013)	(.011)	(.012)	(.008)	(.025)
$15 Price Premium	–.151***	–.206***	–.166***	–.192***	–.164***	–.186***	–.185***	–.145***
	(.018)	(.019)	(.014)	(.018)	(.014)	(.015)	(.011)	(.029)
Respondent Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent Clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,585	4,844	6,289	5,069	6,394	6,057	11,057	2,151

Notes: This table reports the results of a logit regression with green plan choice as the binary dependent variable. Marginal effects are reported with standard errors in parentheses. Only the Qualtrics panel sample is included. Columns 1 and 2 report the results when the sample is split into those below and above the median income level, respectively. Columns 3 and 4 report the results when the sample is split into those below and above the median education level, respectively. Columns 5 and 6 when the sample is split into those below and above the median NEP scale, respectively. Columns 7 and 8 report the results when the sample is split based on whether the respondent reported being an existing green plan customer.
*** significance at 1% level; ** significance at 5% level; * significance at 10% level

APPENDIX E: PRICE VOLATILITY MANIPULATIONS

Price Volatility Manipulation	Possible Monthly Price	Chance of Price	Variance	Range
Low Volatility (LV)	- $5 $0 + $5	5% 90% 5%	2.5	$10
Medium Volatility/Low Dispersion (MV-LD)	- $15 $0 + $15	20% 60% 20%	90	$30
Medium Volatility/High Dispersion (MV-HD)	- $30 $0 + $30	5% 90% 5%	90	$60
High Volatility/Low Dispersion (HV-LD)	- $15 $0 + $15	40% 20% 40%	180	$30
High Volatility/High Dispersion (HV-HD)	- $30 $0 + $30	10% 80% 10%	180	$60

Notes: This table displays the five specific price volatility manipulations we used with the corresponding variance and range of each price distribution, as part of the larger data collection process. All the prices displayed in the table are depicted relative to the expected monthly price of each plan; therefore, changes in the premium of the green plan just shifted the entire price distribution by the amount of the price premium, which does not change the variance or range of the distribution.

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Both publications have earned SCIMago Journal Ratings in the top quartile for Economics and Econometrics publications.

IAEE wishes to congratulate and thank all those involved including authors, editors, peer-reviewers, the editorial boards of both publications, and to you, our readers and researchers, for your invaluable contributions in making 2019 a strong year. We count on your continued support and future submission of papers to these leading publications.