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An Experimental Study of the Effect of Monetary Incentives and Fees on Consumer Energy Behavioral Intentions

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Abstract

Residential electricity consumption is responsible for a significant portion of greenhouse gas emissions each year in the United States. Conserving energy and increasing demand for renewable energy sources are two ways individuals can help reduce the negative impacts of electricity consumption. Research on monetary incentives and fees has demonstrated their potential to encourage pro-environmental behaviors, but knowledge of their effects on sustainable energy behaviors in particular is incomplete. In this study, an investigation of three levels of incentives and fees framed to encourage either energy conservation or investment in renewable energy is conducted to determine their effect on consumer energy behavioral intentions. Through a survey that exposed participants to incentives and fees on bill graphics, participants' perceptions and intended future behaviors were measured. Data were collected about consumers' willingness to pay to participate in clean energy programs, invest in solar panels, and upgrade to efficient appliances. Results of the survey experiment show that exposure to low levels of incentives and fees significantly increased participants' intentions to participate in pro-environmental behaviors and willingness to pay for solar panels when compared to a control group, while high incentive and fee values were no longer effective. Moderate and high incentive and fee levels were, however, effective in increasing participants' perceived costs and benefits from participating in energy-efficient behaviors. Finally, the framing of the incentives and fees was not found to be significantly influential with respect to participant perceptions and intended energy behaviors.

Keywords: Consumer behavior; Electricity markets; Incentives and fees; Pro-environmental behavior

1 Introduction

In the United States, 60% of electricity comes from burning fossil fuels, and electricity production was responsible for a quarter of all greenhouse gas emissions in 2020 [1]. While individuals cannot bear all responsibility for taking action to reduce emissions and combat climate change, there is significant potential for individuals to reduce energy consumption. Greenhouse gases and other emissions from electricity can be significantly curtailed if enough individuals take actions such as the following: reducing electricity consumption [2], installing solar panels [3], upgrading to energy efficient appliances [4], and participating in renewable energy credit programs [5].

Researchers and environmental programs have identified incentives as an impactful way to encourage energy conservation and other clean energy behaviors. Incentives provide an individual something beneficial following a behavior [6], such as offering a monetary reward, rebate, or coupon for reducing home energy consumption. Research suggests incentives offer an effective tool for promoting behavior change [7–9], and incentives and fees have proven effective in encouraging pro-environmental energy behaviors specifically [10–12]. The incentives literature predominantly focuses on positive reinforcement (i.e., adding an appealing stimulus, such as money, to increase the likelihood of future behavior). However, despite findings showing that individuals value losses more heavily than gains [13], negative reinforcement (e.g., fees for undesirable energy behavior) in this domain remains largely untested. It has been shown that consumer energy decisions are sometimes not economically rational and conflict with people's beliefs and material interests [14], indicating a need for a better understanding of consumer energy behavior in response to financial interventions.

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Given the nature of electricity markets, financial motivators such as monetary incentives and fees can be naturally implemented to modify consumer energy behaviors. Nevertheless, the challenge lies in designing incentive and fee policy structures that motivate the desired behaviors in a cost-effective way. Research has shown that in some instances the effectiveness of incentives and fees depends on their magnitudes [15]; in some cases, the absence of an incentive or fee produces more favorable results than paying or charging people small amounts of money, while in other cases, high-value incentives or fees do nothing to improve or even hinder performance.

This study features a survey experiment conducted to analyze the effects of various levels of monetary incentives and fees on consumer energy decisions. Effects on intended energy conservation, through stated intentions to reduce energy use or install energy-efficient appliances, and investment in renewable energy sources, through stated intentions to install solar panels or opt into renewable energy credit programs, are measured. The survey experiment was designed to address the following research questions:

(1) How do various levels of monetary incentives or fees influence self-reported attitudes and intended behaviors regarding household electricity choices?
(2) How does the framing of monetary incentives and fees, e.g., as motivators to reduce energy consumption vs. invest in renewable energy and as gains vs. losses, influence self-reported attitudes and intended behaviors regarding household electricity choices?

The experimental data generated by the experiment will provide a quantitative understanding of the impacts of financial interventions on intended consumer choices. This will be valuable for conducting policy and tradeoff analyses as well as for modeling and simulating consumer behavior in electricity markets. The combination of experimental studies using human subjects with system models of market systems can provide recommendations for future researchers and practitioners in this domain. These results could also be extended or generalized to support modeling of consumer environmental behavior in other, non-energy domains.

2 Methodology

This study employed an experimental survey designed to measure the perceptions and intended behaviors of individuals following their exposure to various levels of monetary incentives and fees on electricity bills. Monetary incentive and fee interventions can be introduced without physically altering existing electricity systems, making near-term implementation feasible. In this study, participants responded to questions about four multi-item measures within the context of electricity markets: perceived norms, intended future energy behaviors, intended one-time energy efficient behaviors, and perceived costs and benefits. Participants also responded to energy-related willingness-to-pay questions along with demographic questions to assess existing behaviors in electricity markets.

The research questions established in Section 1 were addressed by quantifying the effects of three levels of incentives and fees on consumers through collecting and analyzing survey data. Specifically, the study was conducted via Amazon's Mechanical Turk (MTurk) platform from February through May of 2022. MTurk is a popular behavioral science tool; it is an online, crowd-sourced employee marketplace that allows participants to complete online tasks in exchange for compensation that can be transferred to their bank accounts or to their Amazon gift card balance [16,17]. CloudResearch, which works directly with MTurk, provides additional features so that researchers can obtain high-quality participants from MTurk and demographic diversity [18]. The university's Institutional Review Board (IRB) approved this research prior to data collection under protocol 2021-005(N).

Potential participants viewed a posting on MTurk that described a one-time study on "attitudes, perceptions, and behaviors." Participants who proceeded to complete the survey were given a cover story to reduce response bias and were told that the study was investigating their familiarity with current events. The survey stated that participants would be "randomly assigned to provide your beliefs about one of the following topics and comment on the presentation of information about that topic." All participants were then told that they were "randomly assigned" to the "renewable energy / energy consumption" condition. After the cover story, participants were actually randomly assigned to one of thirteen conditions, each of which presents a graphic showing an electric bill with rebates or fees that vary by condition. After viewing the bill graphic associated with their assigned condition, participants responded to attention checks to ensure their understanding of the manipulation. These checks asked participants about the type of bill they viewed, whether their bill was greater or less than that of the previous month, and the reason their bill changed. Next, they responded to questions about their perceptions, beliefs, and intentions, followed by some demographic questions. At the end of the study, participants were debriefed and compensated for their time.

The experiment used a between-subjects design in which participants were randomly assigned to one of the thirteen following conditions: (i) control bill (CB); (ii) low incentive for reducing energy use (LIR); (iii) moderate incentive for reducing energy use (MIR); (iv) high incentive for reducing energy use (HIR); (v) low incentive for investing in renewable energy (LII); (vi) moderate incentive for investing in renewable energy (MII); (vii) high incentive for investing in renewable energy (HII); (viii) low fee for not reducing energy use (LFR); (ix) moderate fee for not reducing energy use (MFR); (x) high fee for not reducing energy use (HFR); (xi) low fee for not investing in renewable energy (LFI); (xii) moderate fee for not investing in renewable energy (MFI); and (xiii) high fee for not investing in renewable energy (HFI). The low, moderate, and high levels of incentives and fees were kept consistent regardless of the way the intervention was framed and were valued at \$15.60, \$31.20, and \$62.40 per month, respectively. The incentives and fees were communicated to participants by showing them a fictional energy bill designed to look similar to electric energy bills from PSE&G, a publicly owned utility company headquartered in Newark, New Jersey. Some bill features were simplified for the purpose of drawing attention to the manipulated parts of the bill.

All bill prices were kept consistent with the exception of the manipulated incentives and fees. The incentive for reducing energy use (IR) was a lower total energy bill due to an "energy saver discount" for households whose energy consumption is no more than 800 kWh per month. The incentive for investing (II) was a lower total energy bill due to a small government-issued subsidy given for having installed solar panels on the home or opting into the utility company's green energy program. The fee for not reducing use (FR) was a higher total energy bill due to dynamic pricing having been implemented by the utility, meaning that the participant had to pay more for some electricity that was used during peak consumption hours. The fee for not investing (FI) was a small government-issued carbon tax that could be avoided if consumers elect to install solar panels, participate in the utility's green energy program, or invest in renewable energy sources in some other way.

Following the manipulations in the survey, participants responded to questions pertaining to their perceptions of norms, intended future behaviors, intended energy efficient behaviors, perceived costs and benefits, and willingness to pay for renewable energy and to conserve electricity. Four multi-item measures were used to create composite scores for the dependent variables, and the remaining questions were used to determine participants' willingness to pay to participate in pro-environmental behaviors such as investing in solar panels, opting into a clean energy program, and upgrading to energy efficient appliances.

- **Perceived Norms (PN):** A five-item measure assessed participants' perceptions of norms (adapted from [19]), on a 1 (strongly disagree) to 6 (strongly agree) Likert scale. Participants were asked whether they agree or disagree with statements such as "Most of my neighbors believe it is morally right to engage in energy behaviors that are beneficial for the environment."
- **Intended Future Behaviors (FB):** An eight-item measure examined intended repeated future energy behaviors (adapted from [20]) on a 1 (never) to 6 (always) scale. Participants were asked how often they expected to engage in behaviors such as "Purchasing eco-friendly products over their less environmentally friendly counterparts" within the next six months. Two of the items were framed in a reverse way where lower is more environmentally friendly (e.g., "leaving the lights on when I am not using them"), to ensure participants did not enter the same response for all items.
- **Efficient Behaviors (EB):** A four-item measure captured participants' intended one-time future energy decisions on a 1 (very unlikely) to 6 (very likely) scale. For example, participants were asked how likely they were to "participate in my power utility's green energy or renewable energy credit program" within the next 6 months. Participants were also able to indicate that they already have made these decisions.
- **Perceived Costs and Benefits (PCB):** A four-item measure examined perceived cost and benefits of pro-environmental behaviors (adapted from [20]) on a 1 (strongly disagree) to 6 (strongly agree) Likert scale. Participants were asked whether they agree or disagree with statements such as "If I did not invest in renewable energy sources by installing solar panels or participating in my utility's green energy program, I would personally incur financial costs."

Three measures of willingness to pay (WTP) were captured through open response and multiple choice questions associated with solar panel installation, clean energy program enrollment, and energy efficient appliance upgrades. The prompts for the solar panel and clean energy program WTP measures asked participants to write in monetary values for the amount they would be willing to invest in a 1,000-Watt solar panel system on their home or property, and the amount they would be willing to pay each month to participate in their utility company's clean energy program. The third WTP measure asked about four appliance categories: refrigerators, clothes washers, clothes dryers, and central air conditioning units. In line with existing Energy Star appliance rebates, participants were asked what rebate amount they would require to replace their existing appliances with Energy Star certified equivalents.

Prior to analyzing the survey responses, composite scores were created using the responses from the PN, FB, EB, and PCB measures. The responses for items within each measure were averaged, resulting in three normally distributed dependent variables on a 1-6 scale. The EB composite scores were normally distributed on a 1-7 scale as respondents could indicate that they already made those decisions. A composite score was also created using the four appliance rebate (AR) questions, however, similar to the WTP for solar panels and WTP for clean energy measures, these responses were not normally distributed. Once the composite measures were created, responses were reviewed to ensure participants ($n = 1,346$) paid attention to the survey and completed it thoroughly. Participants (n =17) were removed for leaving one or more of the dependent variables blank and (n =11) for failing at least half of the attention checks, indicating inattention to the survey and manipulations. Participants remaining in the study included 1,318 residents of the United States with a mean age of 40.01 ($SD = 12.75$). Figure 1 includes an overview of the demographics of the study participants.

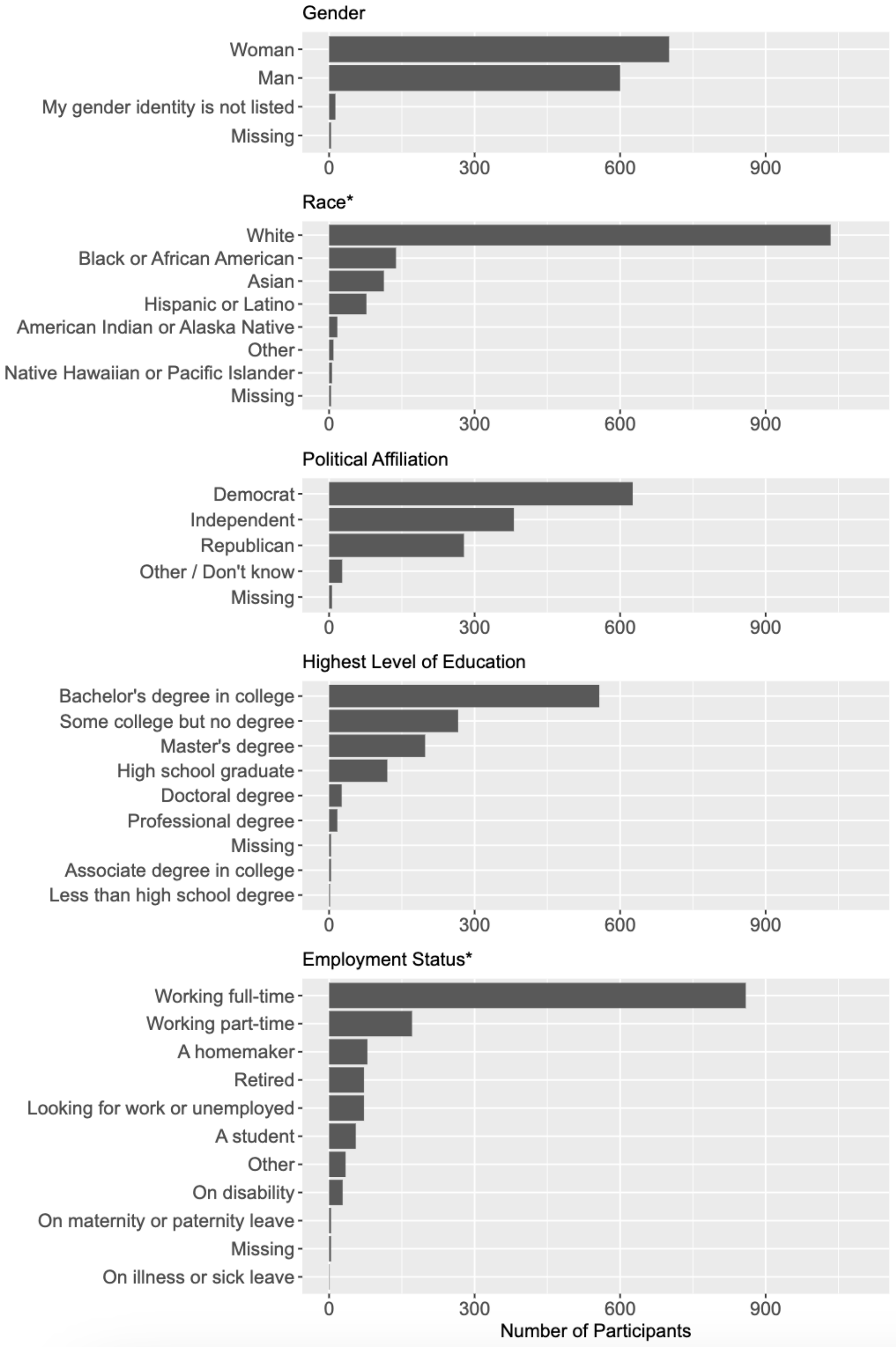

Fig. 1. Participant demographics; note that respondents were able to select multiple racial identities and employment statuses.

Following the calculation of the composite scores and the removal of inadequate responses, summary statistics were generated, and statistical analyses were performed. To determine how the levels and framing of incentives and fees influenced participant responses, multi-variate analyses of variance (MANOVAs) were conducted by grouping responses based on the experiential condition, the type of incentive or fee, and the level of the incentive or fee with the four normally distributed composite dependent variables (PN, FB, EB, and PCB). In the case of a significant MANOVA result, individual analyses of variance (ANOVAs) were conducted for each of the dependent variables to determine whether they varied significantly among one or more conditions, incentive or fee groups, or levels. In instances where the ANOVAs were significant, t-tests were used to determine which conditions, groups, or levels had significant differences from the control. Kruskal-Wallis tests, the non-parametric equivalent of ANOVA tests,

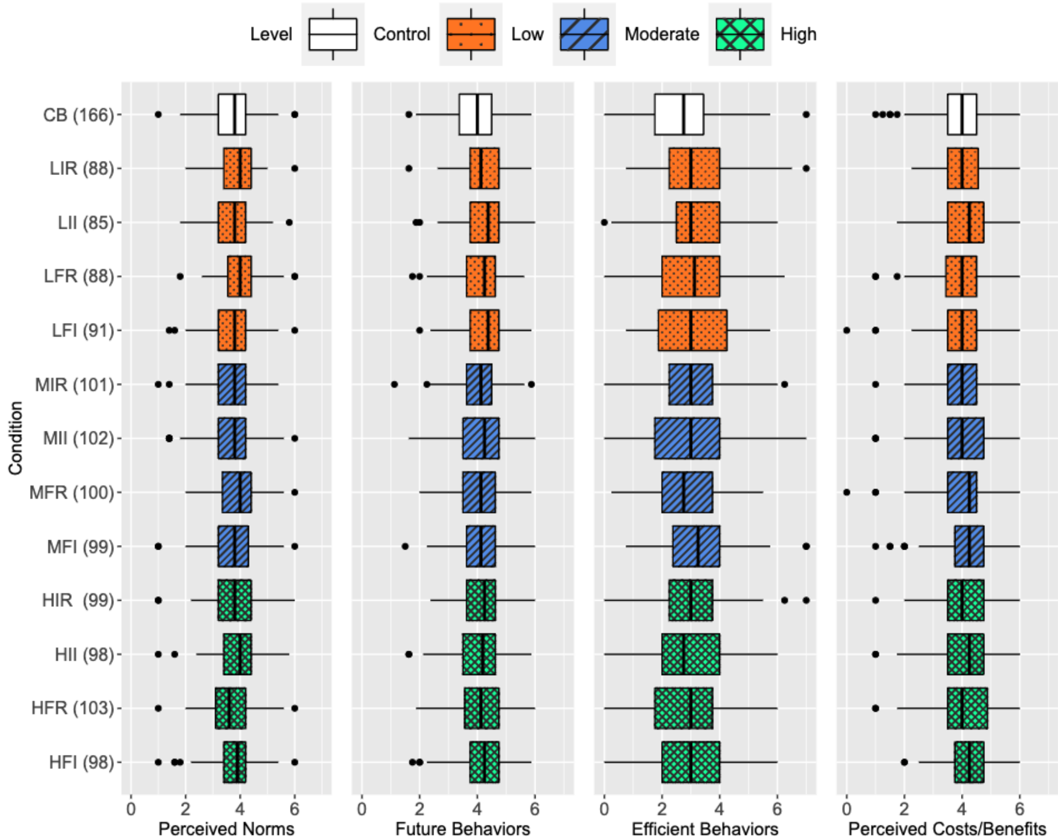

Fig. 2. Box and whisker plots showing minimum, median, maximum, interquartile range, and outliers for each dependent variable (columns) across each condition (rows). The number of observations is included in parentheses next to the condition label on the y-axis for each of the conditions. Experimental conditions include control bill (CB), low incentive for reducing energy use (LIR), low fee for not investing in renewable energy (LFI), low incentive for investing in renewable energy (LII), low fee for not reducing energy use (LFR), moderate incentive for reducing energy use (MIR), moderate incentive for investing in renewable energy (MII), moderate fee for not reducing energy use (MFR), moderate fee for not investing in renewable energy (MFI), high incentive for reducing energy use (HIR), high incentive for investing in renewable energy (HII), high fee for not reducing energy use (HFR), and high fee for not investing in renewable energy (HFI).

were conducted with the WTP for solar panels, WTP for clean energy, and AR responses to compare the responses across conditions, groups and levels. Significant Kruskal-Wallis tests were followed by Mann-Whitney tests, the non-parametric equivalent of *t*-tests.

3 Results and discussion

The the minimum, median, maximum, interquartile range, and outliers for each condition of the perceived norms, intended future energy behaviors, intended one-time energy efficient behaviors, and perceived costs and benefits measures are shown in box and whisker plots in Figure 2. Figure 2 highlights the fact that the median score and distribution of each measure does not vary significantly between most experimental conditions. To further quantitatively evaluate the differences in means for these measures, MANOVA tests were conducted to check for significant differences among all 13 conditions, the five incentive and fee groups (Control, IR, II, FR, FI), and the four incentive and fee levels (Control, L, M, H). As shown in Table 1, the Levels MANOVA showed statistically significant differences across conditions (p=0.0168), while those of the Conditions and Groups did not, indicating that the conditions in these latter distinctions did not significantly alter the dependent variables. Following the significant MANOVA results for the Levels, ANOVAs were conducted for each of the dependent variables, with the results provided in Table 2.

According to Table 2, the future behaviors (FB), efficient behaviors (EB), and perceived costs/benefits (PCB) ANOVA tests produced statistically significant results ($p < 0.005$), whereas the perceived norms (PN) variable showed no significant differences across incentive and fee levels. To further explore the dependent variables with significant ANOVAs, *t*-tests were conducted to determine which incentive and fee levels had mean values that varied significantly from the control condition. The *t*-test results, shown in Table 3, revealed that the FB means for the low

Table 1. Results of MANOVAs with all composite dependent variables for comparison of all conditions, incentive and fee groups, and incentive and fee levels.

	df	Pillai's Trace	*F*	*p*-value
Conditions				
Condition	12	0.048492	1.3345	0.0615
Residuals	1305			
Groups				
Group	4	0.017717	1.4603	0.1048
Residuals	1313			
Levels				
Level	3	0.018654	2.0538	0.0168*
Residuals	1314			

Signif. codes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 2. Results of the Levels ANOVAs for each dependent variable.

	df	Sum Squared Error	Mean Squared Error	*F*	*p*-value
Perceived Norms					
Level	3	1.04	0.34661	0.524	0.6658
Residuals	1314	869.19	0.66149		
Future Behaviors					
Level	3	7.18	2.39228	3.6109	0.0129 *
Residuals	1314	870.55	0.66252		
Efficient Behaviors					
Level	3	151	5.004	2.8399	0.0368 *
Residuals	1314	2315.29	1.762		
Perceived Costs/Benefits					
level	3	8.34	2.78054	3.1762	0.0234 *
Residuals	1314	1150.33	0.87544		

Signif. codes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3. Results of future behaviors (FB), efficient behaviors (EB), and perceived costs/benefite (PCB) *t*-tests between incentive and fee levels and the control condition.

Condition	Control mean	Experimental mean	*t*	*p*-value
Future Behaviors				
Low	3.944	4.187	-3.101	0.002**
Moderate	3.944	4.078	-1.719	0.087
High	3.944	4.128	-2.341	0.020*
Efficient Behaviors				
Low	2.712	3.065	-2.908	0.004**
Moderate	2.712	3.007	-2.519	0.012*
High	2.712	2.942	-1.947	0.052
Perceived Costs/Benefits				
Low	3.869	4.028	-1.838	0.067
Moderate	3.869	4.104	-2.72	0.007*
High	3.869	4.114	-2.868	0.004**

Signif. codes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

and high incentive and fee levels differ significantly from the control condition, with respective p-values of 0.002 and 0.020; the EB means for the low and moderate incentive and fee levels differ significantly from the control condition, with respective p-values of 0.004 and 0.012; and the PCB means for the moderate and high incentive and fee levels differ significantly from the control condition, with respective p-values of 0.007 and 0.004.

Table 4. Participants' stated willingness to pay (WTP) to invest in a 1,000-Watt solar panel system and monthly WTP to participate in a clean energy program.

	Min	25th percentile	Median	Mean	75th percentile	Max
Solar Panels (SP)	0	150	500	1,249	1,500	10,000
Clean Energy (CE)	0	0	10	23.26	20	1,000

Addressing the research questions from Section 1, the framing of the monetary incentives and fees had no statistically significant influence on attitudes, perceptions, nor intentions. This indicates that participants did not respond differently to incentives and fees designed to motivate energy conservation vs. investment in renewable energy nor gains vs. losses. The levels results, on the other hand, are interesting because they are not consistent across dependent variables. For the FB responses, low- and high-valued incentives and fees influenced participants intentions; however, the middle ground was not influential. When making one-time energy decisions, participant EB responses increased in the presence to low- and moderate-valued incentives and fees, but became saturated once the value reached a certain level. Finally, at least the moderate level of incentives and fees was required to significantly alter the PCB responses, and the influence of the intervention remained at the high value. This is further evidence that incentives and fees need to be carefully designed and implemented to elicit desired behaviors. It is interesting to learn that the levels were effective while the framing was not, given the behavioral tendency to assign more weight to losses than gains in equivalent scenarios [13]. This lack of influence could be due to the nature of this study and might not persist if participants were financially responsible for paying the fees presented on the bill graphics. It is also possible that the incentives and fees were not large enough to induce loss aversion. These results could be extended by conducting a field experiment with electric utility customers and implementing the incentives and fees from this study.

As mentioned previously, participants also responded to other energy-related questions, including their WTP to install a 1,000-Watt (W) solar panel system on their home and their WTP each month to participate in a clean energy or renewable energy credit program with their utility provider. Table 4 includes summary statistics of the survey responses. Participants stated a median WTP of $500 with a mean of $1,249 for a 1,000W solar panel system. The large difference between the median and the mean is the result of a relatively small number of participants responding with a willingness to invest very large amounts of money. To participate in a renewable energy credit program or clean energy program with their utility company, participants reported a median WTP of $10 per month with a mean of $23.26 per month. Again, the mean is much larger than the median due to a small number of very high response values.

The survey also gauged consumers' WTP to upgrade their refrigerator, washing machine, clothes dryer, and central air conditioning units to Energy Star certified appliances, with and without rebates. Figure 3 displays the distributions of participant responses, where many responded that they either already have upgraded to efficient appliances or would be willing to do so without any rebate. Participants were able to respond that they already have an Energy Star certified [refrigerator/washing machine/clothes dryer/central air conditioning unit] or that they do not own a [refrigerator/washing machine/clothes dryer/central air conditioning unit] at all. For each of the appliances, less than 5% of participants responded that they would not replace their existing appliances with Energy Star certified alternatives regardless of the rebate offered.

To evaluate the differences in the WTP measures, Kruskal-Wallis tests were conducted for each of the conditions, groups, and levels. According to the results in Table 5, only the condition comparison and level comparison of the WTP for solar panels responses varied significantly between conditions/levels with p-values of 0.043 and 0.014, respectively. To better understand the influence of the incentive and fee conditions and levels, Mann-Whitney tests were performed between the control condition and each of the incentive and fee conditions as well as between the control condition and each of the levels. The results from these tests are included in Table 6.

According to the Mann-Whitney results, the LIR, LII, LFR, and MFI conditions all varied significantly from the control condition. Similarly, the low inventive and fee level resulted in significantly different solar panel WTP amounts when compared to the control condition. Each test produced a $p-$value lower than 0.05. These results indicate an interesting observation that incentives and fees in smaller amounts could boost intended WTP to install solar panels, and similar to the earlier results, the framing of the incentive or fee did not matter. This aligns with Kamenica's findings [15], which suggest that high-value incentives and fees do not always result in more significant behavior changes than their low-value counterparts.

4 Conclusion

This study describes a new experimental and analytical procedure to quantitatively evaluate the influence of different levels of monetary incentives and fees on electricity attitudes, perceptions, and intentions. The data collected were used to uncover information about United States residents' intentions to conserve electricity, upgrade to energy

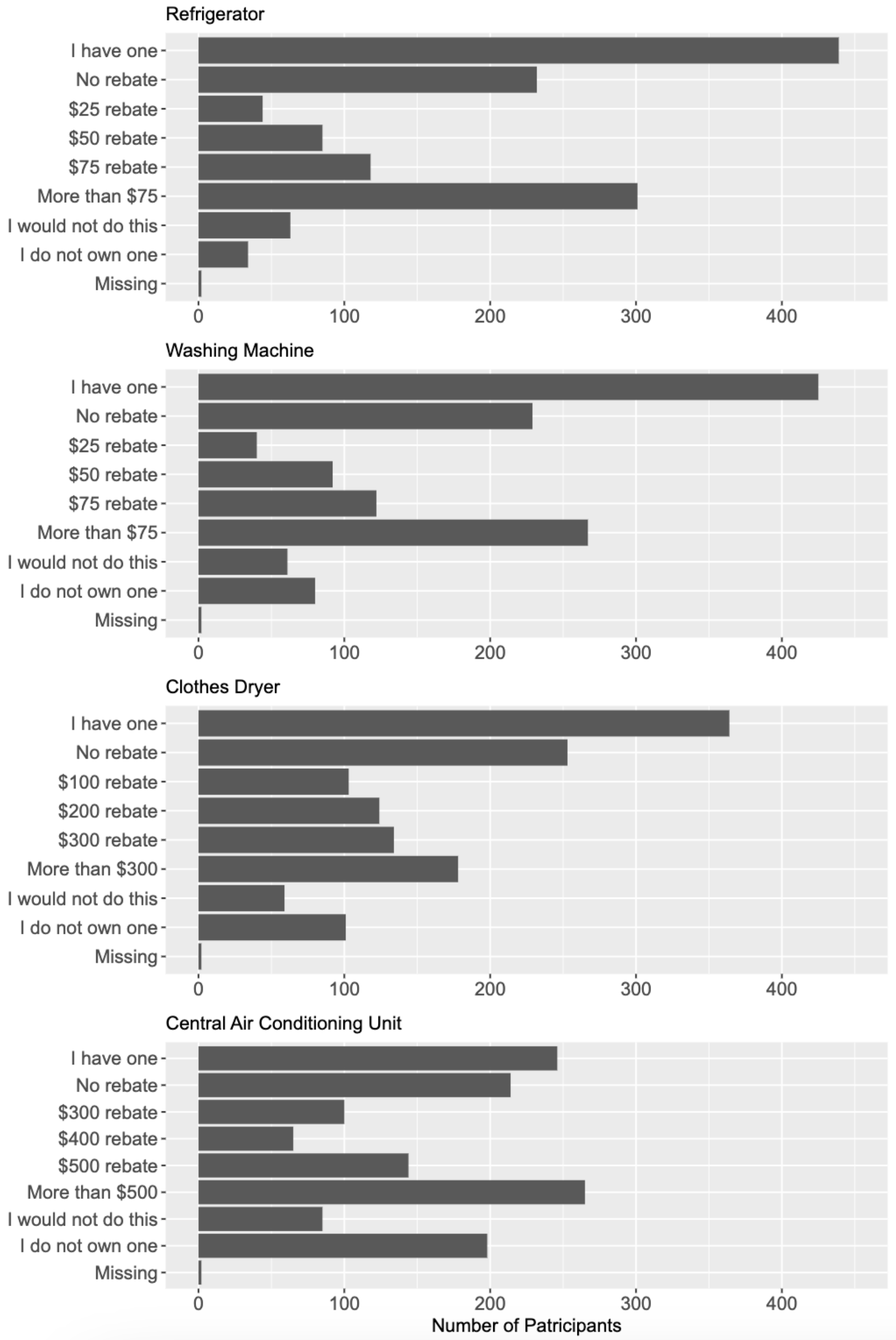

Fig. 3. Participants' willingness to pay for energy efficient appliances, in response to multiple choice questions: "To replace my [appliance] with an Energy Star certified [appliance] I would need my utility company to provide:"

efficient appliances, invest in solar panels, and pay to participate in renewable energy credit programs. The results compare different incentive and fee framing techniques along with the effectiveness of three levels of incentive and fee monetary amounts. The comparison of the different incentive and fee interventions uncovered interesting consumer behavior tendencies. For example, lower levels of incentives or fees on electricity bills were found to induce an increased intention to make efficient energy decisions and an increased WTP for solar panels, whereas higher levels of incentives and fees were required to influence participants' perceived costs and benefits when making pro-environmental energy decisions. The results presented in this study are limited by the fact that participants did not truly experience gains or losses through the incentive and fee conditions assigned to them and similarly were not responsible for participating

Table 5. Results of Kruskal-Wallis tests for the solar panel (SP), clean energy program (CE), and appliance rebate (AR) willingness to pay (WTP) variables comparing conditions, incentive and fee groups and incentive and fee levels.

	df	chi-squared	*p*-value
Conditions			
CE - Condition	12	14.456	0.273
SP - Condition	12	21.548	0.043*
AR - Condition	12	7.048	0.854
Groups			
CE - Group	4	4.163	0.384
SP - Group	4	6.983	0.137
AR - Group	4	0.33	0.988
Levels			
CE - Level	3	3.186	0.364
SP - Level	3	10.68	0.014*
AR - Level	3	1.301	0.729

Signif. codes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6. Results of solar panel (SP) willingness to pay (WTP) Mann-Whitney tests between experimental incentive and fee conditions and the control bill (CB) condition.

Condition/Level	W	$p-$value
Conditions		
Low Incentive Reduce	5580.5	0.002**
Low Incentive Invest	5679	0.011*
Low Fee Reduce	5971	0.016*
Low Fee Invest	7049	0.373
Moderate Incentive Reduce	7899	0.426
Moderate Incentive Invest	7971.5	0.419
Moderate Fee Reduce	7675	0.301
Moderate Fee Invest	6593	0.007*
High Incentive Reduce	7465	0.21
High Incentive Invest	7508.5	0.293
High Fee Reduce	7758	0.199
High Fee Invest	9675	0.052
Levels		
Low	24280	0.002**
Moderate	30139	0.068
High	29706	0.058

Signif. codes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

in the behaviors required to receive any rewards or penalties. Likewise, since the behavioral responses were stated instead of measured, there is potential for response bias in the results. Since this study focuses on perceptions and intentions, future research that studies observed, rather than stated, behavioral responses to incentives and fees would help to further quantify the role of incentives and fees in eliciting pro-environmental electricity behaviors.

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