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Investigating the Efficacy of Government Rebates: A Case of the Smart Irrigation System

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Government rebates provide monetary incentives to encourage consumers' adoption of eco-friendly technologies. Understanding how consumers perceive the value of rebate is crucial to policy makers. We use the smart irrigation system as an example and design choice experiments that present rebates in two formats: the total device cost and the cost consumers needed to pay versus the total device cost and the rebate value. We find that consumers discount the value of the rebate more when presented with rebate value. Additionally, the framing of incentives has a spillover effect on the perceived value of a seemingly unrelated attribute (i.e., water saving).

Key words: choice experiment, eco-friendly technology adoption, framing effect

Introduction

Various eco-friendly technologies—such as solar photovoltaics, light-emitting diodes, and water-efficient washing machines and toilets—are available to households. These technologies are expected to reduce negative externalities on the environment and save household expenditures in the long term. Several studies have conducted cost–benefit analyses of energy-efficient technologies. For instance, Granade et al. (2009) conducted a cost–benefit analysis of energy-saving technologies for US industries, businesses, and residents. They concluded that an investment of $520 million in energy-saving technologies would save $1.2 trillion in energy expenditures over 10 years. Schweitzer (2005) conducted a meta-analysis of Weatherization Assistance Program studies and estimated that weatherization costing approximately $2,600 could reduce natural gas costs by approximately $260 annually.[1] Despite the benefits of eco-friendly technologies, their rate of adoption has not been as high as expected (Greene, German, and Delucchi, 2009).

Government subsidies, usually in the form of rebates that compensate consumers for the cost of installing eco-friendly devices, are potentially useful to encourage eco-friendly technology adoption. Pérez-Urdiales and Baerenklau (2019) examined whether rebate programs in Southern California resulted in investments in water-efficient technologies that would not have occurred otherwise. They found that rebate programs increased investment in water-efficient technologies and the adoption of some unsubsidized water-efficient technologies, which they referred to as the "acceleration effect." Huh et al. (2019) estimated that a 10% rebate for energy-efficient rice cookers reduced electricity by 83.88 GWh per year in South Korea. Datta and Filippini (2016) concluded that rebate programs

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[1] However, Allcott and Greenstone (2012) argued that previous studies likely underestimate technology adoption costs and thus overstate the benefit of energy-saving technologies.

increased the sales share of ENERGY STAR household appliances by 9%–18% in the United States between 2001 and 2006.

The effectiveness of rebates in promoting eco-friendly technologies is expected as long as consumers are price sensitive; however, the efficacy of rebates (i.e., whether consumers perceive a rebate as equivalent to the same amount of price reduction) is understudied. Munger and Grewal (2001) documented that a rebate and a price discount with equal monetary values may not be perceived equally by consumers. They showed that conventional discounts (direct reductions in prices) are more favorable to consumers than a rebate of the same dollar amount. If consumers prefer direct price cuts over rebates, incentives should be presented in the form of price cuts rather than rebates.

In this article, we estimated the efficacy of rebates using a set of choice experiments and the smart irrigation system as an example. We estimated the rate of substitution between the rebate value and price, which measures how much a rebate is discounted or magnified relative to its monetary value. The rate of substitution was estimated for two rebate scenarios to examine the framing effect. Previous studies have suggested that various promotion practices are not perceived equally by consumers even if they generate the same amount of monetary value. Several studies have compared consumers' perceived values of price discounts (in percentage or value) with extra product promotion (e.g., "buy one get one free") or a "mixed" promotion strategy (e.g., buy two get 50% off) when offers have the same unit cost (Diamond, 1992; Sinha and Smith, 2000; Smith and Sinha, 2000; Hardesty and Bearden, 2003; Palazon and Delgado-Ballester, 2009; Lowe, 2010; Chen et al., 2012; Liu and Chiu, 2015). Related to the abovementioned studies, Harlam et al. (1995), Yadav (1995), and Janiszewski and Cunha (2004) examined the effect of promotion formats for bundled sales (i.e., variations of mixed promotion strategy) and suggested that the perceived value of a discount is reference dependent.

In addition to the framing effects of promotions, previous findings demonstrate that at the same level of monetary value, consumers' preference for discount formats may be dependent on the sizes of discounts (Hardesty and Bearden, 2003; Palazon and Delgado-Ballester, 2009; Liu and Chiu, 2015), the perceived performance risk of products (Lowe, 2010), and the price level of products (Smith and Sinha, 2000). Existing studies have also provided further insights into why consumers may discriminate between discount formats. For instance, Çakır and Balagtas (2014) provided evidence that consumers are less responsive to package size changes than to price changes. Additionally, Diamond and Campbell (1989) and Diamond and Sanyal (1990) noted that price promotions are likely to be framed as reduced losses and may affect the reference price, while bonus pack promotions are likely to be framed as gains. In such a case, prospect theory (Kahneman and Tversky, 1979) predicts that a reference-dependent preference will likely differentiate price discounts, bonus packs, and mixed promotions because these promotions are perceived as avoiding losses or receiving gains, and they also have effects on reference prices.

Another body of studies examined whether discounts presented in percentage versus absolute terms resulted in different value perceptions or purchase intentions (Heath, Chatterjee, and France, 1995; Chen, Monroe, and Lou, 1998; Gendall et al., 2006; McKechnie et al., 2012; González et al., 2016). These studies showed that consumers' perceived value of discounts may depend on product price (González et al., 2016) and discount size (Gendall et al., 2006; McKechnie et al., 2012). Studies have found that consumers' responses and discount value perceptions are affected by the induced cognitive costs when evaluating promotions (Andersen, 2015; Sargent et al., 2018; Mo et al., 2019).

In contrast, this study examined the framing effect of two rebate formats, which has not been studied by previous literature. In both formats, participants were presented with the same original price for a device. The monetary values of rebates were the same. The only difference between the two formats was that participants in the first format were presented with their own costs after the rebate, while participants in the second format were presented with the rebate amount. The two formats differed only in semantic phrasing and were otherwise identical. The two formats represent popular rebate formats, and we aimed to evaluate whether consumers discriminate between them.

We expected such information to be important for determining the best rebate format to encourage the adoption of new technologies.

This study makes the following contributions. First, we designed a set of choice experiments that allowed us to estimate the marginal rate of substitution (MRS) between price and rebate and to examine the potential nonequivalence of two rebate formats. This insight provides valuable marketing guidance regarding which rebate format is more effective. We documented how much the rebate value was discounted when the incentive was presented as the device cost and own cost versus the device cost and rebate. In addition, we present evidence that although the water-saving attribute was presented in the same way in the two rebate formats, rebate framing introduced spillover effects on consumers' willingness to pay (WTP) for the water-saving attribute. We found that spillover was prevalent in our sample and had a significant impact on consumers' willingness to adopt the smart irrigation system. Based on existing studies, we also discuss the plausible underlying reasons for the behavior changes caused by rebate framing.

Second, the findings of this study have important policy and marketing implications for eco-friendly technology adoption. Our choice experiments used the smart irrigation system for home lawns as an example. Consumers' adoption of smart irrigation systems for home lawns has significant environmental benefits. Lawns in the United States constitute an important part of the urban landscape and cover a large area (Milesi et al., 2005). Smart irrigation systems use weather data to automatically adjust watering schedules to meet specific landscape needs. Unlike traditional automatic irrigation systems that operate on a preset programmed schedule, smart irrigation controllers use local weather conditions, past weather, and weather forecasts to automatically adjust the lawn-watering schedule. These controllers can improve outdoor water-use efficiency compared to conventional irrigation systems (Zhang and Khachatryan, 2019). We estimated the price premium consumers are willing to pay for devices that can save water. Finally, we identified consumers' heterogeneous preferences and market segmentation in terms of their preferences for rebate and smart irrigation system attributes.

Experimental Design and Estimation Strategy

Experimental Design and Data

Estimating the efficacy of government rebates and consumers' WTP for water saving requires the estimation of the MRS between rebates and prices or water savings and prices. Choice experiments have been used to accurately capture MRS, often in the form of consumer WTP (i.e., the MRS between product attributes and price). Lusk and Schroeder (2004) found that the marginal WTP estimated by choice experiments (i.e., the difference in WTP for two products) is consistent. Yue and Tong (2009) found that the estimated WTP difference between hypothetical and nonhypothetical choice experiments is 7.5%–9.0%, significantly lower than the bias in most contingent valuation studies identified by List and Gallet (2001). Carlsson and Martinsson (2001) and Murphy et al. (2005) also found that choice experiments effectively reduce hypothetical bias. A recent meta-analysis by Penn and Hu (2018) found that choice experiments effectively mitigate hypothetical bias.

Before completing the choice experiments, we first presented participants with an introduction to smart irrigation systems:

> The smart irrigation system uses weather data to adjust watering schedules automatically to meet specific landscape needs. These controllers significantly improve outdoor water-use efficiencies. Most models are easy to integrate and connect with the existing irrigation system.

After reading the introductory information, participants were instructed to select the best choices for eight different choice scenarios. Each scenario consisted of two options simulating a government rebate program promoting the use of smart irrigation systems.

Table 1. Example of Choice Scenarios

Panel A. Version 1

Attributes	Option A	Option B	Option C
Irrigation controller cost	$300	$400	I do not choose either A or B
Water-saving percentage	20%	30%	
Your cost	$75	$100	

Panel B. Version 2

Attributes	Option A	Option B	Option C
Irrigation controller cost	$300	$400	I do not choose either A or B
Water-saving percentage	20%	30%	
Rebate	$225	$300	

Table 2. Levels of Attributes

Attribute	Attribute Levels		
Irrigation controller cost	$200	$300	$400
Water-saving percentage	20%	30%	50%
Your cost	$50	$75	$100

Notes: The levels of the rebate value in each version 2 choice scenario were the differences between the irrigation controller cost and the consumer's own cost, so versions 1 and 2 were equivalent in terms of rebate values.

We designed two versions of choice experiments, with each simulating a rebate format. In the first version, participants were presented with pre- and post-rebate prices, while in the second version, participants were presented with the pre-rebate price and the rebate amount. Both versions of the choice experiment consisted of eight choice scenarios. Each scenario included two options, A and B. Each option represented a smart irrigation system with information about three attributes: total cost, the participant's own cost after rebate or the rebate amount, and the percentage of water saving. Participants were asked to choose the option they preferred. If they did not like either Option A or Option B, they could choose Option C: "Neither Option A nor Option B." Participants were told that the rebates would be covered by government subsidies. They were also told about the expected water savings generated by the smart irrigation system. Table 1 provides examples of the two versions of the choice experiment. As the examples demonstrate, each scenario in version 1 had a corresponding scenario in version 2 that had exactly the same irrigation controller cost, water-saving percentage, and rebate amount (version 2) of the same value as the total cost minus the participant's own cost in version 1 such that versions 1 and 2 differed only in how the rebate was framed.

Each attribute in a given choice scenario had three levels. Table 2 presents the levels for each attribute. An optimal D-efficiency design was employed to determine the eight choice scenarios. An online survey was distributed by Qualtrics™ to homeowners in metropolitan areas of Minneapolis—St. Paul, Minnesota, in 2020. Many studies have used the Qualtrics™ panel to investigate consumer behavior and consumer preferences. For example, Chen and Cheng (2019) studied consumer responses to fake news about brands on social media using a Qualtrics™ -formulated sample. Siew, Minor, and Felix (2018) used a Qualtrics™ sample to explore the influence of the perceived strength of brand origin on consumers' willingness to pay more for luxury goods. Approximately 4,900 people viewed our survey, and a total sample of 2,077 participants completed the choice experiment. We had three screening criteria: Participants had to be 18 years of age or older; they had to live in the seven-county Twin Cities metropolitan area, and they had to have a home lawn that they were responsible for maintaining. To ensure data quality, we included an attention check question in the survey asking participants to select a specific response from the available options; those who failed the check were excluded from the final sample.

Econometrics Model

The choice experiment data were analyzed using a mixed logit model, which relaxes the independence of irrelevant alternatives (IIA) assumption (Revelt and Train, 1998; McFadden and Train, 2000). We assume a linear utility function,

$$U_{ijt} = \boldsymbol{x}'_{ijt}\boldsymbol{\beta}_i + \varepsilon_{ijt}, \tag{1}$$

which specifies individual i's ($i = 1, 2, \ldots, N$) utility from selecting alternative j ($j = 1, 2$) in a choice set t ($t = 1, 2, \ldots, 8$). Each alternative j has a predetermined total device cost, water-saving percentage, and individual i's own cost, which are denoted by the vector $\boldsymbol{x}_{ijt}$. Individual i chooses the most preferred alternative in each choice set t or opts out when neither Option A nor B is preferred to the status quo. The utility of opting out is normalized to 0 in the estimation. The random parameter vector $\boldsymbol{\beta}_i$ denotes the marginal utility parameters corresponding to the attribute vector, $\boldsymbol{x}_{ijt}$. The random parameter vector $\boldsymbol{\beta}_i$ follows some density function $f(\boldsymbol{\beta}|\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of the parameters that define the distribution. In this study, the density function $f(\boldsymbol{\beta}|\boldsymbol{\theta})$ is assumed to be multivariate normal, with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Sigma}$. In the estimation, we assume there is no correlation between the parameters (i.e., $\boldsymbol{\Sigma}$ is diagonal).

This study also examined how participants' characteristics impact their choices. After incorporating individual heterogeneous tastes, equation (1) becomes

$$U_{ijt} = \delta_{jt} + \xi_{ijt} + \varepsilon_{ijt}, \tag{2}$$

where $\delta_{jt} = \boldsymbol{x}'_{jt}\boldsymbol{\beta}$ captures the mean utility of choosing alternative j in scenario t. The term ξ_{ijt} represents the individual-specific random utility, which is assumed to have mean $\boldsymbol{z}'_i\boldsymbol{\alpha}$ and some variance determined by $\boldsymbol{\Sigma}$, where z_i denotes a vector of individual characteristics interact with attributes and vector $\boldsymbol{\alpha}$ captures the effects. The error term, ε_{ijt}, is assumed to be independently and identically distributed following a type I extreme value distribution. Let y_{ijt} denote the response of individual i to alternative j in choice scenario t, namely, $y_{ijt} = 1$ if the alternative is chosen and $y_{ijt} = 0$ if not. For the specification of equation (1) $V_{ijt} = \boldsymbol{x}'_{ijt}\boldsymbol{\beta}_i$, and $V_{ijt} = \delta_{jt} + \xi_{ijt}$ for the specification of equation (2). The likelihood of individual i choosing alternative j of choice scenario t given $\boldsymbol{\beta}_i$ is

$$L_i\left(y_i \mid x_i, \beta_i\right) = \Pi_{t=1}^{T}\Pi_{j=1}^{J}\left[\frac{\exp\left(v_{ijt}\right)}{\sum_{j=1}^{J}\exp\left(v_{ijt}\right)}\right]^{y_{ijt}}. \tag{3}$$

Equation (3) is the likelihood function contributed by individual i. The unconditional likelihood function can then be defined as

$$L = \int_{\theta\in\Theta} L_i\left(y_i \mid \boldsymbol{x}_i, \boldsymbol{\beta}_i\right) f\left(\boldsymbol{\beta}_i \mid \boldsymbol{\theta}\right) d\boldsymbol{\beta}_i, \tag{4}$$

where $f(\cdot)$ is the density function of a multivariate normal distribution with parameter $\boldsymbol{\theta} \in \Theta$. We applied 1,000 Halton draws of $\boldsymbol{\beta}_i$ from the distribution $f(\boldsymbol{\beta}_i|\boldsymbol{\theta})$ to simulate the integral in equation (3). The parameters $\boldsymbol{\theta}$ were estimated by a maximum likelihood estimation.

The main empirical specification of equation (1) for our experimental design is as follows:

$$U_{ijt} = \beta_p p_{ijt} + \beta_r r_{ijt} + \beta_s s_{ijt} + \varepsilon_{ijt}, \tag{5}$$

where p_{ijt} is the smart controller price; r_{ijt} is the rebate and $r_{ijt} = p_{ijt} - c_{ijt}$, which is the difference between smart irrigation system's price and individual i's own cost, c_{ijt}; and s_{ijt} is the percentage of water saving. Rebate r_{ijt} is an attribute that is expected to generate positive utility and offset the disutility of price. Equation (5) indicates that the perceived value of the rebate relative to the smart irrigation system's price can be defined as $W_{r,p} = -\beta_r/\beta_p$, intuitively, the willingness to pay for the rebate.[2] If $-\beta_r/\beta_p > 1$, then the value of the rebate is amplified; if $-\beta_r/\beta_p < 1$, then the rebate value is discounted. Finally, the WTP for the percentage of water savings can be defined as $W_{s,p} = -\beta_s/\beta_p$. The estimated βs are random parameters that are assumed to be normally distributed with the estimated means and standard deviations, and the estimated standard deviations measure the distribution of individuals' WTP. We applied the bootstrapping method to simulate the empirical distribution of the WTP estimates.

Further, this study identifies consumer segmentation using the latent class logit model (Boxall and Adamowicz, 2002; Greene and Hensher, 2003). The latent class analysis assumes that consumer preferences can be classified into Q classes based on demographics, attitudes, and preferences, such that preferences are heterogeneous across different classes, and members of each class have homogeneous preferences. Specifically, suppose individual i belongs to class q ($q = \{1,\dots,Q\}$) with probability

$$\pi_{iq} = \frac{\exp(z_i \boldsymbol{\gamma}_i)}{\sum_{l=1}^{Q} \exp(z_l \boldsymbol{\gamma}_l)}, \tag{6}$$

Where $\boldsymbol{\gamma}$ denotes the class membership parameter with $\boldsymbol{\gamma}_1$ set to 0. Individuals within the same group are assumed to have homogeneous taste parameters; thus, the taste parameter $\boldsymbol{\beta}_i$ for individuals in class q has a density function of $f(\boldsymbol{\beta}_i|\boldsymbol{\gamma}) = \pi_{iq}$. We can then write individual i's contribution to the likelihood function as

$$L_i(y_i \mid x_i, z_i) = \sum_{q=1}^{Q} \pi_{iq} \left\{ \Pi_{t=1}^{T} \Pi_{j=1}^{J} \left[\frac{\exp\left(\boldsymbol{x}'_{ijt}\boldsymbol{\beta}_q\right)}{\sum_{l=1}^{J} \exp\left(\boldsymbol{x}'_{ljt}\boldsymbol{\beta}_q\right)} \right]^{y_{ijt}} \right\}. \tag{7}$$

Both the mixed logit and latent class logit models were estimated with the R package "gmnl" via maximum likelihood estimation (R Core Team, 2022; Sarrias, Daziano, and Croissant, 2020).

Results

Summary Statistics

Participants assigned to version 1 or 2 of the rebate format were independently recruited, with sample sizes of 1,294 and 784, respectively. Table 3 presents the summary statistics of the two samples. The differences between the two samples were minimal, except that the age distribution of version 2 participants was slightly younger than that of version 1 participants.[3] The corresponding summary statistics from the 2019 American Community Survey (ACS) are also included for reference in Table 3. The age distribution of the two samples was slightly shifted toward the younger categories compared to the ACS. Participants tended to have at least some level of higher education and a higher income level. Participants were more likely to be female and married, and the mean and median household sizes were 2.75 and 2.00 people, respectively. The labor force participation rate of the respondents' household was slightly higher compared to the ACS (i.e., approximately 70% of the sample compared to 64.6% from the ACS).

In addition to basic demographics, we gathered information on participants' turfgrass maintenance knowledge. The majority of participants knew their home lawn grass type and soil type. We also asked whether the participants had an automatic irrigation system. We expected that consumers' perceived utility and thus the perceived value of a rebate may depend on their status quo.

[2] Note that in practice, we assume that both β_r and β_p are independent random parameters with estimated mean and standard deviation. Thus, the $W_{r,p}$ is a random variable formed as the ratio of two normally distributed parameters. In the later section, we use 1,000 bootstraps to simulate the distribution of $W_{r,p}$ and interpret the results based on the simulated distribution.

[3] In the estimation, we included the full set of demographic variables to control for potential demographic differences between the two samples.

Table 3. Summary Statistics of Choice Experiment Participants

	Version 1		Version 2		ACS 2019
	Frequency	Percentage	Frequency	Percentage	(%)
Know grass type					
No	419	32.41	292	37.24	
Yes	874	67.59	492	62.76	
Know soil type					
No	488	37.74	307	39.16	
Yes	805	62.26	477	60.84	
With auto irrigation					
No	838	64.81	520	66.33	
Yes	455	35.19	264	33.67	
Age					
18–45	500	38.67	398	50.77	38.46
46–65	527	40.76	260	33.16	33.47
66 and over	266	20.57	126	16.07	28.07
Education level					
High school or lower	183	14.15	115	14.67	40.55
Some college	317	24.52	209	26.66	24.02
College Graduates	477	36.89	294	37.50	29.14
Graduate and higher	316	24.44	166	21.17	6.28
Gender					
Male	461	35.65	257	32.78	49.51
Female	832	64.35	527	67.22	50.49
Married					
Yes	802	62.03	413	52.68	59.69
No	491	37.97	371	47.32	40.31
Household with child					
Yes	257	19.88	183	23.34	33.16
No	1036	80.12	601	76.66	66.84
Income level					
Low (<$50,000)	334	25.83	209	26.66	35.66
Median ($50,000–$100,000)	554	42.85	358	45.66	39.00
High (>$100,000)	405	31.32	217	27.68	25.35
Labor market status					
Full time	581	44.93	373	47.58	64.60
Part time	171	13.23	122	15.56	
Unemployed	127	9.82	63	8.04	
Student	45	3.48	38	4.85	35.40
Retired	335	25.91	167	21.30	
Not in labor force	34	2.63	21	2.68	

Notes: The sample of this study was restricted to homeowners with home lawns, aged 18 and older, without a home well and living in the Minneapolis–St. Paul–Bloomington Metropolitan Area. The sample for the ACS was restricted to people aged 18 years and older who lived in the Minneapolis–St. Paul–Bloomington Metropolitan Area.

Table 4. Random Parameter Logit Coefficients, Without and With Demographic Interactions

	Version 1, Own Cost Format		Version 2, Rebate Format	
	Model I Estimate	**Model II Estimate**	**Model III Estimate**	**Model IV Estimate**
Intercept	3.888***	3.481***	2.616***	2.448***
	(0.155)	(0.147)	(0.202)	(0.200)
Irrigation controller cost	−2.721***	−3.114***	−0.994***	−1.243***
	(0.235)	(0.237)	(0.320)	(0.328)
Water saving percentage	10.417***	3.046	12.815***	6.890**
	(0.488)	(1.960)	(0.757)	(2.714)
Rebate	2.468***	2.388***	1.396***	0.966*
	(0.254)	(0.392)	(0.352)	(0.526)
sd. Intercept	7.825***	6.811***	6.339***	5.651***
	(0.218)	(0.194)	(0.256)	(0.243)
sd. Controllercost	1.759***	1.087***	1.668***	1.500***
	(0.054)	(0.045)	(0.073)	(0.080)
sd. Savingperc	12.986***	18.690***	14.456***	14.905***
	(0.402)	(0.537)	(0.597)	(0.633)
sd. Rebate	0.539***	0.188	0.377**	0.786***
	(0.111)	(0.158)	(0.173)	(0.151)
Demographics control	No	Yes	No	Yes

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively. Cost is in $100. The likelihood ratio test of Model II versus Model I has a χ^2 value of 120.1 and p-value < 0.001. The likelihood ratio test of Model IV versus Model III has a χ^2 of 96.3 and p-value < 0.001. Models II and IV interact rebate and water-saving marginal utility with demographics (i.e., age group, education level, gender, marital status, household size, living with children or not, income level, and employment status).

For instance, participants without an automatic irrigation system may perceive the smart irrigation system as unnecessary. In contrast, participants with automatic irrigation systems may be more willing to upgrade to smart irrigation systems. As Table 3 indicates, the majority of participants did not have an automatic irrigation system.

Mixed Logit Estimation Results

The summary statistics of the responses to the choice experiments are presented in the appendix. Table 4 presents the estimation results using mixed logit models. Model I in Table 4 corresponds to the specification of equation (5) and estimates for participants completing choice experiment version 1 (i.e., participants were informed about the pre-rebate price and their own costs). The corresponding results for participants who completed choice experiment version 2 are presented as Model III. To further demonstrate that our conclusions are robust, Models II and IV allowed the mean marginal utility of rebate and water saving to be a linear function of demographics and corresponded to Models I and III, respectively. The likelihood ratio test results indicated that the models that incorporated demographic variables (i.e., Models II and IV) had better goodness of fit. Thus, we focus on reporting the results derived from Models II and IV. As expected, the coefficient for price is negative and significant in both models, indicating that the increase in price generates significantly negative marginal utility. The coefficient for rebate is positive and significant, indicating that participants receive a positive and statistically significant utility from the rebate.

To determine whether rebate framing has an impact on the participants' perception of rebate value, we need to estimate the rebate-to-price ratio. If the ratio is greater than 1, the rebate value is amplified. If the ratio is less than 1, the rebate value is discounted. Recall that choice experiment

Table 5. Rebate Discounting/Amplifying Factor and WTP for Water Savings Based on Mixed Logit Model Estimation Results

	Version 1, Own Cost Format			Version 2, Rebate Format		
	1st Quantile	Median	3rd Quantile	1st Quantile	Median	3rd Quantile
		Model I			Model III	
WTP rebate	0.557	0.830	1.328	-0.547	0.571	1.228
WTP water saving	0.093	3.419	7.352	-3.290	5.233	14.310
		Model II			Model IV	
WTP rebate	0.625	0.781	1.031	-0.094	0.410	0.983
WTP water saving	−3.056	0.805	5.130	-5.374	2.738	11.617

Notes: The empirical WTP distribution was generated via 1,000 bootstrapping draws from the estimated parameter distribution. Wilcoxon test results: WTP Rebate Model I versus Model III had a p-value < 0.001; WTP Rebate Model II versus Model IV had a p-value < 0.001; WTP Water Saving Model I versus Model III had a p-value = 0.0319; WTP Water Saving Model II versus Model IV had a p-value < 0.001.

versions 1 and 2 differed only in how the rebate was presented. The difference between the two versions' estimated rebate-to-controller cost ratios was merely due to framing effects.

Typically, the MRS is estimated as the ratio of estimated coefficients. For example, Models II and IV suggest that the MRS between rebate and price is 0.77 (i.e., $-(2.388/-3.114)$) and 0.78 (i.e., $-(0.966/-1.243)$), respectively. It appears that the effect of the rebate format is negligible. However, the standard deviations are large and different, as indicated in our results. Thus, when evaluating the rebate-to-cost ratio (i.e., $-\beta_r/\beta_p$), we further use bootstrap simulations to estimate the first, second, and third quartiles of the WTPs to see how the WTPs were distributed.

Table 5 shows the simulated distribution of the rebate to cost MRS with 1,000 bootstrapping of β_p and β_r from their estimated independent normal distributions. Table 5 presents the first, median, and third quantiles. As the results indicate, when presented with controller cost and own cost (i.e., version 1), rebates were discounted at 0.78 (median). When presented with controller cost and rebate value (version 2), rebates were discounted at 0.41 (median). In addition, when examining the first and third quantiles, we observed that the rebate-to-cost ratio distribution was shifted to the right when presented with version 1. We performed the Wilcoxon test to examine whether the empirical distributions of the discounting factors between versions 1 and 2 were significantly different. The test rejected the null hypothesis that they were equally distributed, with a p-value of < 0.001. The result indicated that participants discounted rebate value less when presented with incentives in the form of their own cost compared to the form of the rebate value.

In addition to altering consumers' perceived value of rebates, we observed that different incentive formats induced different levels of estimated consumer WTP for water saving. Recall that the water-saving attributes of the two versions were exactly the same. Table 5 indicates that the empirical distribution of WTP for water saving had a higher median ($2.74 per 1% water saving) in version 2 compared to version 1 ($0.81 per 1% water saving). The difference in the median WTP for water saving between the two versions was very close with or without demographic variables: approximately $1.9. Finally, the first and third quantiles of the empirical distribution indicated that when presented in the format of rebate value, the WTP estimates for water saving were more spread out (i.e., a higher interquartile range and thus higher variation).

Latent Class Logit Estimation Results

We employed a latent class analysis to further investigate participants' segmentation regarding their responses to framing effects and WTP for water-saving technology. Table 6 presents the marginal utility estimations for the latent class logit model with three classes. We interacted the price and rebate value with survey version to allow price sensitivity and rebate valuation parameters in

Table 6. Estimation Results from Latent Class Logit Model

	Group I Estimate	Group II Estimate	Group III Estimate
Intercept	-2.517^{***}	-4.686^{***}	3.623^{***}
	(0.158)	(0.371)	(0.104)
Irrigation controller cost	2.570^{***}	-1.737^{***}	-3.120^{***}
	(0.452)	(0.569)	(0.243)
Water saving percentage	10.162^{***}	9.160^{***}	2.772^{***}
	(0.902)	(0.931)	(0.432)
Rebate	-2.490^{***}	1.497^{**}	2.614^{***}
	(0.489)	(0.600)	(0.275)
Controller cost × Version 2	-2.216^{***}	0.730	−0.242
	(0.704)	(1.156)	(0.325)
Water saving × Version 2	3.930^{**}	-6.038^{**}	2.240^{***}
	(1.556)	(2.453)	(0.658)
Rebate × Version 2	2.740^{***}	−0.360	0.065
	(0.775)	(1.411)	(0.398)
Membership probability (%)	49.64	21.14	29.23

Notes: Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively. Cost is in $100.

equation (5) to vary by survey version. The number of classes was selected based on the Bayesian information criterion (BIC) and Akaike information criterion (AIC). When the number of classes increased from two to three, the BIC and AIC values decreased significantly (from ~24,000 to ~20,000, decreases of 15.7% and 16.7%, respectively). When the number of classes increased from three to four, the BIC and AIC values decreased only slightly (decreases of 3.9% and 3.0%, respectively). Given the minimal improvements in AIC and BIC by adding one additional group, we selected the three-class model for our analysis.

Table 7 presents the class-specific coefficients of the three-class model. Group I participants consisted of 49.6% of the sample. They were not sensitive to price. The estimated positive marginal utility of price is not uncommon (e.g., Ouma, Abdulai, and Drucker, 2007). A positive marginal utility of price indicates that this group of participants perceived the smart irrigation system as an investment, and disutility from the price did not exceed their utility from getting a smart irrigation system. This group of participants had a strong preference for the water-saving attribute. Further, this group of participants was sensitive to the effect of framing. Note that framing incentives as rebates made the marginal utility of price and rebate close to 0, while the marginal utility of water savings was amplified. This may indicate that participants in Group I tended to rely on water savings to make smart irrigation system choices when incentives were framed as rebates.

Group II participants (21.1% of the sample) were price sensitive, had positive values for water-saving technology, and were responsive to rebates. Regardless of how the incentives were presented, Group II participants had positive utility from water saving. However, when incentives were presented as rebates, their preference for water-saving technology was significantly reduced, while the framing effect on price and rebate utility was not statistically significant. Group III participants constituted 29.2% of the sample. This group of participants was sensitive to price, and both water savings and rebates could bring positive utilities to them. In contrast to Group II participants, Group III participants' preference for water-saving technology was amplified by the framing effect, but framing did not affect their utilities from price and rebate value.

Table **??** presents the coefficients for demographics in the class membership function. Compared to participants in Group I, participants in Groups II and III were more likely to know their grass type, and participants in Group III were less likely to know their soil type. There was no statistically

Table 7. Coefficients of Demographic Variables from the Latent Class Membership Function

Reference Level	Variable	Class II Estimate	Class III Estimate
	Intercept	−0.8235***	−0.9878***
		(0.1115)	(0.1063)
	Know grass type	0.1229***	0.1614***
		(0.0466)	(0.0435)
	Know soil type	−0.0563	−0.1881***
		(0.0450)	(0.0422)
	With auto irrigation	−0.0305	−0.0073
		(0.0445)	(0.0415)
Age 18–45	Age 46–65	0.2062***	0.000016
		(0.0531)	(0.0513)
	Age 66 and over	0.1746**	−0.0012
		(0.0734)	(0.0682)
High school or lower	Some college	−0.1034	−0.0366
		(0.0688)	(0.0647)
	College diploma	0.1474**	0.1410**
		(0.0658)	(0.0643)
	Graduate and higher	−0.1523**	0.0916
		(0.0737)	(0.0698)
Female	Male	0.0628	0.2600***
		(0.0461)	(0.0410)
Not married	Married	−0.2687***	−0.0660
		(0.0493)	(0.0452)
No children	With children	0.0257	0.1786***
		(0.0645)	(0.0596)
	Household size	0.0058	0.0854***
		(0.0173)	(0.0162)
Low income	Mid-income	−0.1202**	−0.0655
		(0.0536)	(0.0505)
	High-income	−0.1270*	−0.1119*
		(0.0653)	(0.0591)
Full time	Part-time	−0.0283	0.1346**
		(0.0652)	(0.0590)
	Others	0.0379	0.0453
		(0.0526)	(0.0490)

Notes: Group I is the reference group. Values in parentheses are standard errors. Single, double, and triple asterisks indicate significance at the 10%, 5%, and 1% level, respectively.

significant difference between the groups in terms of the possession of automatic irrigation systems. Compared to Group I participants, Group II participants tended to be older, have a college diploma but not a graduate or higher degree, be less likely to be married, and have lower income. Compared to Group I, Group III participants were more likely to have a college diploma, be male, have children, have a larger household size, be less likely to have a high income, and be more likely to be working part-time.

The latent class analysis provides further insights into the behavior changes caused by framing. The findings suggest that in approximately 50% of the sample (i.e., Group I), the participants relied much more on the water-saving percentage for decision making when incentives were presented as rebates. For them, the importance of price and rebate decreased significantly when incentives were presented as rebates. This result suggested that the spillover of framing to seemingly unaffected attributes was prevalent. On the other hand, for the other 50% of the sample, the rebate format shifted consumers' preference to adopt the smart irrigation system without shifting their price and rebate utility (i.e., for Groups II and II). Recall that survey versions 1 and 2 differed only in how the incentives were framed, while the water-saving attribute was presented in the same way. If rebates shifted participants' willingness to adopt smart irrigation systems, the interaction term between the survey version and water savings would capture such a shift. Thus, the effect of framing on the preference for water-saving technology could be because rebates encouraged or discouraged the adoption of smart irrigation systems. Specifically, for Group II, with price and rebate value perception unaffected, their adoption of the smart irrigation system was discouraged by the rebate. Thus, it appeared that their preference for water saving was reduced. In contrast, Group III's adoption of the smart irrigation system was encouraged by the rebate; thus, their preference for water-saving technology appeared to increase.

Conclusions and Discussion

Various technologies that reduce negative environmental impacts are available on the market. The realization of the environmental benefits of such technologies depends on the speed of technology adoption. Using rebates to generate monetary incentives to encourage consumers' adoption of eco-friendly technologies is a popular policy choice. The results derived from choice experiments presented in this study suggest that the efficacy of rebates is associated with how they are framed. We find that, with the same monetary incentives, consumers discount the rebate value less when the incentive is in the form of the device cost and own cost (version 1). Specifically, when presented with version 1, the mixed logit estimation results suggest that the perceived value of a rebate is discounted at a factor of approximately 78%, while when presented in the format of version 2, the perceived value of a rebate is discounted at a factor of approximately 41%. Such prominent differences highlight the importance of taking framing effects into account when designing government rebate programs. The effect of framing could be because the device cost and own cost format is perceived as a direct price reduction. Our finding is consistent with Munger and Grewal (2001), who found that price cuts are more favorable to consumers than rebates. Another plausible explanation is that version 1 is a simpler discount format that does not require consumers to conduct any calculation. Previous studies have found that the increased mental effort associated with the promotion format induces lower preferences (Suri, Monroe, and Koc, 2013).

In addition to the framing effect on the perceived value of rebates, we find that the semantic phrasing of rebates affects the perceived value of a seemingly unrelated attribute, water saving. The estimated WTP for water saving suggests that although the water-saving attribute was presented in the same manner for the two versions of the choice experiments, presenting the incentive in the format of rebate value increased consumers' median WTP by approximately \$1.9, and the effect was statistically significant. Two factors may be at play. First, when presented with an incentive in the form of rebate value, consumers are required to make calculations for their own cost. It is likely that this effort of calculation makes price play a less important role in consumers' decision making.

This finding is supported by the estimation results in Table 4, which show that the marginal disutility from price and the marginal utility from rebate are both reduced. In addition, it is possible that when calculation is needed, the increased mental effort may drive consumers to rely more on the level of water saving to make decisions and put less importance on price. We emphasize that this spillover effect of framing could be very significant. Although presenting rebates in the form of price cuts is preferred by consumers, the increased WTP for unrelated attributes could be significant enough to offset the framing effect. When examining the choice percentages presented in the appendix, we find that the opt-out probability is larger in version 1. This result highlights that the spillover effect of framing may be worth further investigation.

Finally, we find that presenting the rebate value introduces variations to price perception. The interquartile range of the estimated empirical distribution of water-saving WTP is significantly enlarged, which indicates that variation in WTP is increased.

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Appendix

Table A1. Choice Experiment Design

Scenarios	Option	Controller Cost	Percentage Water Savings (%)	Own Cost	Rebate
1	1	300	20	75	225
1	2	400	30	100	300
2	1	300	30	100	200
2	2	200	20	75	125
3	1	200	20	50	150
3	2	400	50	75	325
4	1	400	30	75	325
4	2	200	20	50	150
5	1	300	50	75	225
5	2	200	30	50	150
6	1	200	20	75	125
6	2	300	50	100	200
7	1	300	30	75	225
7	2	200	20	50	150
8	1	400	50	100	300
8	2	300	30	50	250

Notes: For the own-cost format, respondents were presented with controller cost and own cost. For the rebate format, respondents were presented with the controller cost and rebate. Each choice scenario also included an opt-out option.

Table A2. Choice Percentages by Scenario and Option

		Choice Probability (%)	
Scenarios	**Option**	**Own Cost Format**	**Rebate Format**
1	1	26.06	19.64
1	2	42.00	58.93
1	Opt out	31.94	21.43
2	1	41.92	61.48
2	2	29.08	19.39
2	Opt out	29.00	19.13
3	1	19.95	13.78
3	2	54.76	69.64
3	Opt out	25.29	16.58
4	1	37.66	59.82
4	2	32.56	21.56
4	Opt out	29.78	18.62
5	1	56.84	70.66
5	2	19.49	14.03
5	Opt out	23.67	15.31
6	1	16.47	10.84
6	2	54.91	71.81
6	Opt out	28.62	17.35
7	1	43.62	61.99
7	2	25.29	18.11
7	Opt out	31.09	19.90
8	1	44.16	63.90
8	2	26.99	17.98
8	Opt out	28.85	18.11

Table A3. Random Parameter Logit Coefficients, Without and With Demographic Interaction, for Participants with Auto Irrigation System

	Version 1, Own Cost Format		Version 2, Rebate Format	
	Model I Estimate	Model II Estimate	Model III Estimate	Model IV Estimate
Intercept	5.729***	6.108***	2.952***	3.140***
	(0.334)	(0.360)	(0.369)	(0.395)
Irrigation controller cost	−2.504***	−2.303***	−0.025	0.096
	(0.404)	(0.412)	(0.563)	(0.583)
Water saving percentage	10.970***	1.259	10.305***	−3.874
	(0.869)	(3.835)	(1.367)	(5.614)
Rebate	2.511***	1.253*	1.050*	0.172
	(0.437)	(0.761)	(0.632)	(1.084)
sd. Intercept	8.011***	8.058***	4.461***	5.093***
	(0.389)	(0.404)	(0.361)	(0.430)
sd. Controllercost	1.922***	2.297***	0.609**	0.829***
	(0.096)	(0.119)	(0.253)	(0.207)
sd. Savingperc	14.384***	9.478***	12.534***	10.079***
	(0.764)	(0.657)	(0.932)	(0.934)
sd. Rebate	0.505**	1.623***	2.051***	1.876***
	(0.199)	(0.142)	(0.202)	(0.209)
With demographic control	No	Yes	No	Yes

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Values in parentheses are standard errors. Cost is in $100. The likelihood ratio test of Model II versus Model I had a χ^2 value of 55.1 and p-value = 0.003. The likelihood ratio test of Model IV versus Model III had a chi-square of 69.6 and p-value = 0.001. Models II and IV interact rebate and water-saving marginal utility with demographics (i.e., age group, education level, gender, marital status, household size, living with children or not, income level, and employment status).

Table A4. Rebate Discounting/Amplifying Factor and WTP for Water Saving, Based on Mixed Logit Model Estimation Results, for Participants with Auto Irrigation System

	Version 1, Own Cost Format			Version 2, Rebate Format		
	1st Quantile	Median	3rd Quantile	1st Quantile	Median	3rd Quantile
		Model I			Model III	
WTP rebate	0.527	0.836	1.389	−3.648	−0.010	3.699
WTP water saving	−0.829	3.245	7.930	−27.553	−0.225	26.714
		Model II			Model IV	
WTP rebate	−0.084	0.342	0.980	−2.209	0.081	2.329
WTP water saving	−2.308	0.320	3.601	−13.018	0.827	14.869

Notes: The empirical WTP distribution was generated via 1,000 bootstrapping draws from the estimated parameter distribution. Wilcoxon test results: WTP Rebate Model I versus Model III had a p-value < 0.001; WTP Rebate Model II versus Model IV had a p-value = 0.0161; WTP Water Saving Model I versus Model III had a p-value = 0.0523; WTP Water Saving Model II versus Model IV had a p-value = 0.1068.