sustainability

MDPI

Article

Relating Knowledge and Perceptions of Sustainable Water Management to Preferences for Smart Irrigation Technology

Dong Hee Suh [1], Hayk Khachatryan [2,3,*], Alicia Rihn [3] and Michael Dukes [4]

1 Department of Food and Resource Economics, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul 02841, Korea; dhsuh@korea.ac.kr

2 Food and Resource Economics Department, University of Florida, 2725 S. Binion Rd, Apopka, FL 32703-8504, USA

3 Mid-Florida Research and Education Center, University of Florida, 2725 S. Binion Rd, Apopka, FL 32703-8504, USA; arihn@ufl.edu

4 Department of Agricultural and Biological Engineering, University of Florida, 205 Frazier Rogers Hall, P.O. Box 110570, Gainesville, FL 32611-0570, USA; mddukes@ufl.edu

* Correspondence: hayk@ufl.edu; Tel.: +1-407-410-6951

Academic Editor: Paul Opdam

Received: 20 February 2017; Accepted: 12 April 2017; Published: 14 April 2017

Abstract: Water quantity and quality concerns in urban environments have prompted conservation groups, governmental agencies, and policy makers to develop and promote residential water conservation programs, including restrictions on residential landscape irrigation practices and incentives for the adoption of water-efficient appliances. Previous literature links household characteristics, financial incentives, and demographic characteristics to the adoption of water-efficient appliances and overall water use. However, relatively little attention has been given toward understanding how homeowners' perceptions and knowledge of smart irrigation technologies affect their preferences or stated purchase likelihood of such irrigation equipment. To address this gap in the literature, this paper identifies perception- and knowledge-related factors that are correlated with the purchase likelihood of smart irrigation controllers. The generalized logit regression model results suggest that knowledge about irrigation systems and residential landscaping are positively correlated with purchase likelihood. Similarly, homeowners' perceptions about conservation efforts, water restrictions, and their neighbors' irrigation habits all increase purchase likelihood. Combined with statistically-significant correlations of several socio-demographic variables and purchase likelihood, these results have theoretical and practical implications, which are summarized in this paper.

Keywords: landscape irrigation; landscape management; water conservation; urban landscaping

1. Introduction and Background

Sustainable water management is becoming more imperative as population growth, climate change, drought, water pollution, and economic growth have increased the demand for water [1,2]. In 2010, U.S. households accounted for 7.6% of all national water use at an average of 88 gallons per capita per day [3]. Currently, the majority (75%) of residential water is being used for outdoor purposes, including landscape irrigation [4,5]. The U.S. Environmental Protection Agency (EPA) estimates that U.S. households use nine billion gallons of water daily to irrigate their landscapes [6]. Irrigation is often necessary to maintain landscape aesthetics and health [2,5]. Thus, residential irrigation efficiency is imperative when considering sustainable water management in urban areas. Well-managed residential landscapes enhance the urban environment and provide economic, environmental and lifestyle/health benefits including erosion/dust control, ground/surface water quality protection, urban heat/noise reduction, carbon sequestration, and psychological well-being benefits [7–11]. Although necessary for plant health, irrigation can have negative environmental and economic consequences when used excessively, including depleting water availability, increasing waterway pollution/contamination due to fertilizer/nutrient runoff and leaching, deteriorating turfgrass/plant health, and increasing homeowners' utility bills [1,12–14]. This is concerning since homeowners often over-irrigate and their irrigation schedules frequently deviate from local irrigation restrictions [15]. The issue is further complicated by 28% of the continental U.S. experiencing moderate to exceptional drought in 2016 [16].

Water scarcity concerns have prompted conservation groups, governmental agencies, and policy makers to develop and promote residential water conservation programs, restrictions, and products, including water-efficient appliances and landscape irrigation practices [6,14,17–23]. For instance, the EPA's WaterSense® Program labels water-efficient products [6]. In Southern California, the SoCal Water$mart Program provides rebates to homeowners who purchase water-efficient products (including turf removal, clothes washers, toilets, rain barrels/cisterns, sprinkler nozzles, soil moisture sensors, and irrigation controllers [21]). Similarly, the Oregon State University's WaterWise Gardening Program promotes using plants and products that use little-to-no water in the landscape [20]. Although these programs offer different incentives and cover diverse products and regions with unique water needs, they all have the same goal of increasing homeowners' use of water-efficient technologies that improve water quality and conserve water resources. In turn, homeowners receive environmental (less water waste) and financial (lower water bills) benefits from installing water-efficient technologies and products [14,24,25]. Previously, research demonstrated that several water conservation policies and programs emphasizing long-term environmental improvement are effective [1] with 19–26% reductions in water usage [26].

With the technological advancements in the past decade, the residential irrigation services industry has gradually transitioned to smart technologies, which improve irrigation system usability while decreasing over-irrigation [27]. Smart irrigation technology utilizes sensors to measure and regulate irrigation based on ambient and soil moisture measures, which is very different from traditional time-based controller systems [27,28]. This information is then available to the homeowner through an in-home station, their smartphone or tablet. There are two main types of smart irrigation controllers: soil moisture sensors (SMS) or evapotranspiration (ET) based controllers. SMS controllers use soil moisture information to regulate/bypass irrigation events based on plant needs [29]. Conversely, ET controllers obtain information from on-site weather stations or local/regional weather networks to determine landscape irrigation requirements [27,28]. Because of local information integration, smart irrigation controllers are generally more efficient than traditional time-based systems [27–30]. Davis and Dukes (2012) estimate that using ET controllers reduces irrigation water use by 63% [27], while Cárdenas-Lailhacar and Dukes (2012) state that SMS controllers reduce irrigation water by 42–72% [29].

However, it is natural to think that water savings will also depend on individual irrigation practices. Admittedly, regional climatic factors are closely related to irrigation usage and ultimately water savings. While some regions require less irrigation due to adequate rainfall and humid weather patterns, others require more irrigation due to drier conditions. However, individual irrigation behavior reflects regional weather patterns because homeowners apply irrigation water onto their landscapes as needed. Due to heterogeneous subjective perceptions of the optimal irrigation level, it is natural that water savings are dependent on individual behavior. In addition, this study focuses on water management for lawns and landscapes in general. Since lawns and landscape composition is controlled mainly by individual preferences, native vegetation was not considered in this study. For instance, homeowners who under-irrigate their landscapes may actually start using more irrigation water with sensor-based technologies. Conversely, those who excessively irrigate will save a considerable amount of irrigation water. The savings of smart irrigation controllers is lower than those of traditional irrigation controllers (typically less than 10%) due to the lack of knowledge by contractors and homeowners [30]. Other studies have found low consumer knowledge about smart irrigation controllers, which hinders their adoption rate [31]. To date, most smart irrigation controller studies focus on performance factors and their water saving potential [15,27,29,30]. In contrast, very few studies have addressed consumers' knowledge of smart irrigation technology and how that influences their purchasing/implementation behavior.

Since consumers' behavior directly affects household water use [14], it is useful to understand what motivates their adoption of water-conserving technologies. Environmental concerns, financial considerations, and household demographics are the main factors influencing consumers' adoption of water-efficient technologies [14,19,24,25,32,33]. Consumers who are more environmentally conscious are more likely to take actions to conserve water, including purchasing water-efficient products [19,25]. In turn, reduced water usage/waste decreases consumers' water bills [14,24]. Therefore, it is not surprising that consumers with water bills based on actual water usage are more likely to adopt water-efficient technologies [19,25]. Estimates indicate that households adopting water-efficient appliances reduce their water usage by 26.6% [24]. Willis et al. (2013) estimate that many water-efficient appliances pay for themselves within two years [14]. Regarding the relationship between socio-demographic characteristics and water conservation technology adoption, studies found that consumers are more likely to purchase water-efficient appliances if they own their home, have a higher income, or a larger household [19,25]. The implications of these studies are that consumers are willing to purchase items that reduce their household water usage and provide axillary benefits. However, consumers' preferences and adoption of new irrigation technologies (e.g., smart irrigation controllers) to reduce water waste in the residential landscapes is not understood.

Previous studies also identify factors and household characteristics that affect water-efficient equipment purchases [24,32] and increase residential irrigation use [14]. These studies suggest that environmental concerns affect consumer preferences for water saving technologies [19,25]. However, relatively little attention was paid to understand how homeowner's knowledge and perceptions affect their preferences or purchase likelihood of smart irrigation technologies. Since relevant irrigation policies are formulated by understanding homeowner's concerns on water-saving technologies, it is necessary to examine the extent to which homeowner's knowledge and perceptions are associated with the purchase likelihood of smart irrigation equipment. Thus, the main purpose of this study was to identify the factors that are correlated with the purchase likelihood of smart irrigation controllers and compare the factors across three geographical areas/states (California, Florida and Texas).

The use of individual perceptions and knowledge in our study can be linked to Ajzen's theory of planned behavior in psychology [34–36]. As Ajzen suggested, individual behavior should be reflected in attitudes, subjective norms, knowledge and perceptions, and environmentally-friendly behavior could be induced by individual beliefs on the importance of sustainable management of the environment. Applying this general theoretical framework to urban landscape management practices, our study tests hypotheses predicting households' behavioral changes with respect to knowledge and perceptions of sustainable water management. Incorporating socio-economic variables, our study uses an econometric technique for discrete choice responses of households.

Based on the findings and research gaps from the previous literature summarized above, the specific hypotheses that were tested are as follows. First, we hypothesize that consumer knowledge about their lawns and landscapes will be positively correlated with their purchase likelihood of smart irrigation controllers (Hypothesis 1). We also hypothesize that knowledge about smart irrigation controllers will be positively correlated with homeowners' purchase likelihood of smart irrigation controllers (Hypothesis 2). The third and fourth hypotheses are that perceptions on water conservation will be positively correlated with the purchase likelihood of smart irrigation controllers (Hypothesis 3) and that perceptions on smart irrigation controllers will be positively correlated with the purchase likelihood of smart irrigation controllers (Hypothesis 4). Further, we hypothesize that demographic characteristics will be associated with the purchase likelihood of smart irrigation controllers (Hypothesis 5) and that the factors that induce the purchase likelihood of smart irrigation controllers will differ across states (i.e., California, Florida and Texas) (Hypothesis 6).

2. Methodology

2.1. Survey and Summary Statistics

The survey was conducted by a third party contractor (Qualtrics Online Survey Software, LLC, Provo, UT, USA) in May 2014 using an online questionnaire, which covered three states: California, Florida and Texas. These three states were selected because they accounted for one-quarter of all U.S. water withdrawals and had issues related to landscape irrigation water management. Moreover, the U.S. Drought Monitor (2016) showed that California and Texas were under moderate, but exceptional drought during 2014. At that time, Florida was not under extreme drought, but had issues related to water shortages and degradation. In order to participate, respondents were screened based on the following criteria: (1) live in a home with a lawn; (2) have an automated irrigation system installed; and (3) do not use smart irrigation sensors (ET, SMS) in their irrigation system. Individuals who met the screening criteria were asked to complete the questionnaire, which took approximately 20 min. The survey was sent to 1000 randomly-selected homeowners in each state (a total of 3000 homeowners). Due to incomplete responses, a total of 2641 homeowners (~88% response rate) completed the questionnaire (873 in California, 881 in Florida and 887 in Texas). Admittedly, the sample may not correspond to the U.S. population because this study targeted individuals with automated lawn irrigation systems. However, the screening criteria were essential because individuals with lawns and irrigation systems (but not smart irrigation) were of interest in the study because the probability of them being concerned and familiar with their household's irrigation water usage was higher than those of people without lawns or irrigation systems. Therefore, the study results correspond to consumers within the core "target market" of the smart irrigation industry.

The survey consisted of three sections. The first section included questions about respondents' existing irrigation practices and general knowledge about characteristics of irrigation systems and residential landscapes. The second section represented respondents' overall knowledge and perceptions about landscape irrigation, smart irrigation systems, and the environment. Lastly, the third section included respondents' socio-economic and demographic information.

Respondents' socio-demographic variables are summarized in Table 1. Most respondents (68.2%) were over 35 years old; 28.9% were 20–34 years old; and 2.8% were less than 20 years old. Similar characteristics were found for California and Texas. Florida's 20–34-year-old group had a slightly higher percentage at 31.8%. Most respondents (87.5%) had obtained a college degree at the time of the study. The majority of respondents were female (62.9%) and had less than one child (76.6%) with "child" defined as less than 18 years old. The 76.6% of households with less than 1 child includes both households without children and those with adult (>18 years) children. This is an important point since a fair number of participants (31.12%) are over 55 years old and may have adult children. Over one-third of the respondents (33.9%) were in the $20,000–$59,999 income category, followed by the $60,000–$99,999 and $100,000–$139,999 category. California and Florida exhibited similar income trends; however, Texas had slightly higher incomes with respondents primarily being in the $60,000–$99,999 category, followed by the $20,000–$59,999 category (Table 1). Although different from the U.S. population, the sample socio-demographics align with the core consumer of lawn and garden purchases (i.e., older, female, married, more educated [37]).

Table 1. Summary statistics of demographic characteristics.

	Full Sample	California	Florida	Texas
Age				
Less than 20	2.84%	3.09%	2.72%	2.71%
20–34	28.93%	28.06%	31.78%	26.94%
35–54	37.11%	35.62%	37.57%	38.11%
More than 55	31.12%	33.22%	27.92%	32.24%
Education				
Less than college degree	12.46%	13.29%	12.83%	11.27%
College degree or higher	87.54%	86.71%	87.17%	88.73%
Gender				
Female	62.85%	62.77%	64.93%	60.88%
Male	37.15%	37.23%	35.07%	39.12%
Number of Kids (<18 years old)				
Less than 1	76.56%	76.29%	77.19%	76.21%
2–3	20.60%	20.85%	19.75%	21.20%
4–5	2.69%	2.63%	2.95%	2.48%
More than 6	0.15%	0.23%	0.11%	0.11%
Household Income				
Less than $19,999	5.04%	5.50%	6.36%	3.27%
$20,000–$59,999	33.85%	32.07%	41.88%	27.62%
$60,000–$99,999	31.16%	29.44%	32.58%	31.45%
$100,000–$139,999	15.98%	17.18%	11.92%	18.83%
$140,000–$179,999	6.47%	7.10%	4.20%	8.12%
$180,000–$299,999	5.64%	7.10%	2.38%	7.44%
More than $300,000	1.86%	1.60%	0.68%	3.27%

Table 2 summarizes respondents' purchase likelihood, knowledge and perceptions regarding smart irrigation technology. With an average score of 4.13 (1 = extremely unlikely; 7 = extremely likely), most respondents were "undecided" on their purchase likelihood of a smart irrigation controller in the next five years. Regarding knowledge about irrigation systems and lawns/landscapes, participants reported relatively low knowledge levels with sprinkler application rates having the lowest level, followed by soil type and then turfgrass/plant types. They were slightly more knowledgeable about turfgrass/plant water needs. Texas respondents indicated a slightly higher level of knowledge for turfgrass/plant types and their water needs. All respondents indicated very low knowledge of smart irrigation controllers with ET-based controllers having the lowest knowledge level followed by SMS-based controllers. Regarding water conservation perceptions, participants agreed with the statement "my state has insufficient water resources and I need to conserve water" the most, followed by "I feel my conservation of water affects the overall supply", "I am aware of water restrictions in my area", and "I often see my neighbors over-irrigating." Respondents were asked about their perceptions of their neighbors' irrigation habits to identify their perceptions of the neighborhood irrigation norms. Californian respondents agreed with the state, conservation and neighbors' statements slightly more than the other states, while respondents from Florida and Texas agreed with the water restrictions statement more than California respondents. When considering participants' perceptions of smart irrigation controllers, respondents indicated that smart irrigation controllers were easier to use and more reliable than conventional controllers. However, smart irrigation controllers were perceived as more expensive than conventional controllers.

Table 2. Variable descriptions.

Variable	Description	Full (*N* = 2641)		California (*N* = 873)		Florida (*N* = 881)		Texas (*N* = 887)	
		M	SD	M	SD	M	SD	M	SD
Purchase likelihood	"When available, how likely is it that you will actually purchase smart irrigation controllers in the next five years?" (1 = Extremely unlikely to 7 = Extremely likely)								
PURCHASE	Likert-type scale	4.13	1.49	4.14	1.48	4.13	1.50	4.11	1.48
Knowledge about irrigation system and lawn/landscape	"How knowledgeable are you about each of the following characteristics of your irrigation system and lawn/landscape?" (1 = not at all knowledgeable to 7 = strongly knowledgeable)								
RATE	Sprinkler application rates	3.39	1.87	3.42	1.88	3.29	1.85	3.44	1.89
TURF	Turfgrass/plant types	3.98	1.84	3.84	1.80	3.97	1.85	4.14	1.87
WATER	Water needs of turfgrass/plants	4.13	1.78	4.12	1.76	4.07	1.82	4.20	1.75
SOIL	Soil type	3.67	1.86	3.73	1.88	3.51	1.84	3.77	1.84
Knowledge about smart irrigation controllers	"How knowledgeable are you about each of the following irrigation controllers?" (1 = not at all knowledgeable to 7 = strongly knowledgeable)								
SMS	Soil moisture sensor (SMS)-based controllers	2.23	1.59	2.29	1.63	2.20	1.56	2.21	1.58
ET	Evapotranspiration (ET)-based controllers	1.97	1.46	2.00	1.48	1.95	1.44	1.95	1.46
Perception on water conservation	"Please indicate your agreement with the following statements." (1 = strongly disagree to 5 = strongly agree)								
CONSERVE	I feel my conservation of water affects the overall supply	3.71	1.05	3.74	1.05	3.70	1.07	3.68	1.04
RESTRICT	I am aware of water restrictions in my area	3.58	1.35	3.32	1.33	3.67	1.31	3.74	1.37
NEIGH	I often see my neighbors over-irrigating	3.23	1.18	3.31	1.18	3.18	1.19	3.20	1.17
STATE	My state has insufficient water resources and I need to conserve water	4.32	0.92	4.53	0.87	4.12	0.95	4.32	0.88
Perception on smart irrigation controllers	"What is your perception of the advantages and disadvantages of conventional vs. smart irrigation controllers?" (1 = conventional controller is better to 7 = smart irrigation controller is better)								
PRICE	Price	3.43	1.76	3.33	1.75	3.53	1.79	3.43	1.74
EASE	Ease of use	4.50	1.70	4.38	1.64	4.54	1.77	4.56	1.68
RELIABLE	Reliability	4.54	1.65	4.45	1.56	4.62	1.69	4.55	1.68

2.2. Generalized Ordered Logit Model

The ordered-response (dependent) variable represents respondents' purchase likelihood of smart irrigation controllers using a seven-point Likert scale (1 = extremely unlikely; 7 = extremely likely). Since the response variable has an ordinal nature, the ordered logit model was used to explore the influence of other factors on homeowners' purchase likelihood of smart irrigation controllers. Previously, the ordered logit model has been used to identify the influence of different variables on consumers' preference and/or purchase likelihood for different products [38–44]. Following the approach used in Suh et al. (2016), the ordered logit model estimates the probability that homeowner i. takes on the value (Y_i) when homeowner i faces the j-th ordered-category for $j = 1, \cdots, M$ where M is the number of categories of the ordinal responses [43]. The ordered logit model is written as follows:

$$P(Y_I > j) = f(X_i\beta) = \frac{\exp(\alpha_j + X_i\beta)}{1 + \exp(\alpha_j + X_i\beta)} \text{ for } j = 1, \cdots, M-1 \quad (1)$$

where $P(\cdot)$ is the probability, $f(\cdot)$ is the probability density function of the standard logistic distribution, X_i is a vector of explanatory variables for homeowner i and α and β represent cut-off and slope parameters, respectively [45,46]. The ordered logit model assumes that the slope parameters (β) do not vary over different alternatives, but the cut-off parameters (α_j) vary over $j = 1, \cdots, M-1$. This is known as the proportional-odds or parallel-lines assumption, which implies that parameters do not change for different categories. That is, the correlation between independent and dependent variables does not vary over the variable categories. However, empirical applications of the ordered logit model frequently violate the parallel-lines assumption [23,47,48]. To relax the parallel-lines assumption, the generalized ordered logit model was developed by Williams (2006), which is written as:

$$P(Y_i > j) = f(X_i\beta_j) = \frac{\exp(\alpha_j + X_i\beta_j)}{1 + \exp(\alpha_j + X_i\beta_j)} \text{ for } j = 1, \ldots, M-1. \quad (2)$$

This allows the slope parameters (β_j) to vary over each category of the dependent variable. That is, this model allows variations for the slope parameters, as well as the cut-off parameters of different categories. In the generalized ordered logit model, the probabilities are expressed as:

$$\begin{gathered} P(Y_i = 1) = 1 - F(X_i\beta_1) \\ P(Y_i = j) = F(X_i\beta_{j-1}) - F(X_i\beta_j) \text{ for } j = 2, \ldots, M-1 \\ P(Y_i = M) = F(X_i\beta_{M-1}) \end{gathered} \quad (3)$$

where $F(\cdot)$ indicates the cumulative density function of the standard logistic distribution. The parameters specified in this model are relevant to the likelihood of the dependent variable [23]. Positive parameters indicate that the explanatory value is likely to increase the probability that the respondents belong to the current or a higher category defined in the dependent variable. On the other hand, negative parameters indicate that the explanatory variable increases the likelihood of the respondent being in the current or a lower category.

3. Results and Discussion

The ordered logit model estimation results were tested for the parallel-lines assumption. Brant's (1990) Wald test was used to check the null hypothesis that all of the estimated coefficients satisfy the parallel-lines assumption, which determines whether the ordered logit model is appropriate for the data [49]. If the null hypothesis is not rejected, the ordered logit model can be used for the analysis. Alternatively, if the null hypothesis is rejected, the generalized ordered logit model is preferred to the ordered logit model [47]. Table 3 summarizes the test results for the parallel-lines assumption. For the full sample, the results show that the null is rejected at the 1% significance level, suggesting that the generalized ordered logit model should be used due to the violation of the parallel-lines assumption. The null hypothesis is rejected for the state-level sub-samples. The test rejects the parallel-lines assumption for the sample of California and Texas at the 1% significance level and 10% significance level for Florida's sample. The results indicate that the generalized ordered logit model is preferred to the ordered logit model. Thus, the generalized ordered logit model is estimated using the maximum likelihood method [45].

The estimated coefficients of the generalized ordered logit model representing the relationships between knowledge levels, perceptions, demographic measures and purchase likelihood of smart irrigation controllers are shown in Tables 4–7. In each table, the first six columns represent the log odds of choosing each category relative to the rest of the categories. The first column shows the log odds of selecting the first category (i.e., category = 1) versus the other categories (i.e., category = 2, 3, 4, 5, 6, 7), and the second column shows the log odds of selecting the first and second categories (i.e., category = 1, 2) versus the other categories (i.e., category = 3, 4, 5, 6, 7). The other columns represent similar comparisons between the categories. The estimates in the first six columns measure the effects of the explanatory variables on homeowners' purchase likelihood of smart irrigation controllers. Only the signs of the estimates are meaningful. The marginal effects are also presented in each table (the last seven columns), which indicate the change in homeowners' possible purchase likelihood with respect to a change in each explanatory variable. The marginal effects provide direct implications of the respondents' knowledge and perceptions on their purchase likelihood of smart irrigation controllers. In the next section, we discuss the marginal effects for the entire sample (H1–H5) and individual states (H6).

Table 3. Brant test for parallel-lines assumption.

Variable [a]	Full Sample			California			Florida			Texas		
	χ^2	$p > \chi^2$ [b]	*d.f.* [c]	χ^2	$p > \chi^2$	*d.f.*	χ^2	$p > \chi^2$	*d.f.*	χ^2	$p > \chi^2$	*d.f.*
ALL	173.62	0.000	85	150.4	0.000	85	108.90	0.085	85	150.05	0.000	85
RATE	6.98	0.222	5	10.73	0.057	5	5.07	0.407	5	3.93	0.559	5
TURF	4.06	0.540	5	9.83	0.080	5	5.03	0.412	5	11.77	0.038	5
WATER	1.69	0.890	5	3	0.700	5	6	0.306	5	3.43	0.633	5
SOIL	7.46	0.189	5	3.73	0.589	5	4.57	0.471	5	19.44	0.002	5
SMS	3.95	0.556	5	12.7	0.026	5	0.98	0.964	5	4.23	0.517	5
ET	4.98	0.418	5	13.87	0.016	5	6.22	0.286	5	4.95	0.422	5
CONSERVE	8.6	0.126	5	6.49	0.262	5	8.98	0.110	5	9.06	0.107	5
RESTRICT	8.78	0.118	5	7.5	0.186	5	4.14	0.530	5	8.74	0.120	5
NEIGH	3.69	0.595	5	5.81	0.325	5	3.76	0.585	5	8.21	0.145	5
STATE	10.85	0.054	5	14.55	0.012	5	13.17	0.022	5	4.13	0.531	5
PRICE	10.36	0.066	5	8.61	0.126	5	6.45	0.265	5	3.73	0.589	5
EASE	7.57	0.182	5	1.24	0.941	5	1.56	0.906	5	8.51	0.130	5
RELIABLE	7.47	0.188	5	9.96	0.076	5	1.4	0.925	5	9.18	0.102	5
INCOME	7.87	0.164	5	2.15	0.828	5	1.93	0.859	5	9.54	0.089	5
AGE	23.28	0.000	5	17.55	0.004	5	13.32	0.021	5	1.82	0.873	5
KIDS	15.59	0.008	5	7.93	0.160	5	10.18	0.070	5	8.77	0.119	5
EDUC	4.82	0.439	5	5.51	0.357	5	1.55	0.908	5	4.69	0.455	5
GENDER	11.96	0.035	5	10.52	0.062	5	10.49	0.062	5	7.17	0.209	5

[a] See Table 1 for variable definitions; [b] a significant test statistic indicates that the parallel regression assumption has been violated; [c] *d.f.* indicates degree of freedom.

Table 4. Estimation results of the generalized ordered linear logit model: full sample.

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [ab]	**1, 2 vs. 3, 4, 5, 6, 7**	**1, 2, 3 vs. 4, 5, 6, 7**	**1, 2, 3, 4 vs. 5, 6, 7**	**1, 2, 3, 4, 5 vs. 6, 7**	**1, 2, 3, 4, 5, 6 vs. 7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
RATE	0.094 (0.064) [b]	**0.138** *** **(0.045)**	**0.084** ** **(0.038)**	**0.071** ** **(0.034)**	**0.145** *** **(0.045)**	**0.217** ** **(0.087)**	−0.003 (0.002)	**−0.011** *** **(0.004)**	0 (0.005)	−0.003 (0.008)	0.003 (0.007)	**0.011** ** **(0.004)**	**0.004** ** **(0.002)**
TURF	0.035 (0.073)	−0.011 (0.053)	−0.037 (0.045)	0.029 (0.041)	0.068 (0.057)	0.071 (0.106)	−0.001 (0.003)	0.002 (0.005)	0.005 (0.006)	−0.014 (0.009)	0 (0.009)	0.006 (0.005)	0.001 (0.002)
WATER	0.024 (0.079)	0.051 (0.055)	0.022 (0.047)	0.062 (0.043)	0.018 (0.059)	0.019 (0.113)	−0.001 (0.003)	−0.004 (0.005)	0.001 (0.006)	−0.011 (0.010)	0.013 (0.010)	0.001 (0.005)	0 (0.002)
SOIL	0.102 (0.070)	**0.134** *** **(0.049)**	**0.139** *** **(0.040)**	0.071 * (0.037)	**0.143** *** **(0.051)**	−0.033 (0.100)	−0.004 (0.003)	**−0.010** ** **(0.004)**	**−0.011** ** **(0.005)**	0.007 (0.008)	0.003 (0.008)	**0.015** *** **(0.005)**	−0.001 (0.002)
SMS	0.16 (0.110)	**0.185** ** **(0.078)**	**0.213** *** **(0.065)**	**0.159** *** **(0.050)**	0.067 (0.060)	0.103 (0.103)	−0.006 (0.004)	**−0.014** ** **(0.006)**	**−0.018** ** **(0.008)**	−0.001 (0.013)	**0.032** *** **(0.011)**	0.005 (0.006)	0.002 (0.002)
ET	**0.248** * **(0.146)**	0.15 (0.096)	0.105 (0.076)	0.047 (0.056)	0.099 (0.064)	−0.002 (0.104)	**−0.009** * **(0.005)**	−0.007 (0.008)	−0.003 (0.010)	0.007 (0.015)	0.001 (0.013)	**0.010** * **(0.006)**	0 (0.002)
CONSERVE	0.068 (0.083)	0.018 (0.059)	**0.105** ** **(0.050)**	**0.145** *** **(0.046)**	0.072 (0.057)	**0.301** *** **(0.106)**	−0.003 (0.003)	0.001 (0.005)	**−0.017** ** **(0.007)**	−0.017 (0.011)	**0.028** *** **(0.010)**	0.002 (0.005)	**0.006** *** **(0.002)**
RESTRICT	0.049 (0.059)	−0.008 (0.043)	−0.022 (0.037)	−0.013 (0.034)	0.036 (0.048)	**0.200** ** **(0.090)**	−0.002 (0.002)	0.003 (0.004)	0.003 (0.005)	−0.001 (0.008)	−0.007 (0.008)	0 (0.004)	**0.004** ** **(0.002)**
NEIGH	0.02 (0.067)	0.067 (0.047)	**0.086** ** **(0.040)**	**0.127** *** **(0.038)**	**0.108** *** **(0.050)**	0.133 (0.090)	−0.001 (0.002)	−0.006 (0.004)	−0.008 (0.005)	**−0.016** * **(0.009)**	**0.020** ** **(0.008)**	**0.008** * **(0.005)**	0.002 (0.002)
STATE	0.016 (0.095)	−0.032 (0.069)	−0.071 (0.060)	−0.052 (0.055)	−0.088 (0.070)	**−0.369** *** **(0.109)**	−0.001 (0.004)	0.004 (0.006)	0.009 (0.008)	0.000 (0.013)	−0.004 (0.013)	−0.002 (0.006)	**−0.007** *** **(0.002)**
PRICE	**0.148** *** **(0.052)**	**0.197** *** **(0.036)**	**0.192** *** **(0.030)**	**0.111** *** **(0.027)**	**0.143** *** **(0.036)**	**0.143** ** **(0.066)**	**−0.005** *** **(0.002)**	**−0.015** *** **(0.003)**	**−0.013** *** **(0.004)**	0.007 (0.006)	**0.012** ** **(0.006)**	**0.012** *** **(0.003)**	**0.003** ** **(0.001)**
EASE	**0.124** ** **(0.057)**	0.060 (0.039)	**0.073** ** **(0.034)**	**0.107** *** **(0.033)**	**0.119** ** **(0.048)**	**0.296** *** **(0.092)**	**−0.005** ** **(0.002)**	−0.002 (0.003)	−0.007 (0.004)	**−0.013** * **(0.007)**	**0.014** * **(0.008)**	0.007 (0.004)	**0.005** *** **(0.002)**
RELIABLE	**0.113** * **(0.058)**	**0.150** *** **(0.040)**	**0.115** *** **(0.035)**	**0.189** *** **(0.034)**	**0.222** *** **(0.049)**	**0.192** ** **(0.090)**	**−0.004** * **(0.002)**	**−0.012** *** **(0.004)**	−0.005 (0.004)	**−0.026** *** **(0.008)**	**0.024** *** **(0.008)**	**0.019** *** **(0.004)**	**0.004** ** **(0.002)**
INCOME	**0.258** *** **(0.067)**	**0.099** ** **(0.042)**	**0.109** *** **(0.036)**	**0.100** *** **(0.033)**	**0.085** * **(0.045)**	0.053 (0.084)	**−0.010** *** **(0.002)**	−0.001 (0.004)	**−0.009** ** **(0.005)**	−0.005 (0.007)	**0.016** ** **(0.007)**	**0.008** * **(0.004)**	0.001 (0.002)
AGE	**−0.603** *** **(0.109)**	**−0.314** *** **(0.070)**	**−0.279** *** **(0.061)**	**−0.205** *** **(0.057)**	**−0.138** * **(0.076)**	0.095 (0.147)	**0.022** *** **(0.004)**	**0.011** * **(0.006)**	**0.016** ** **(0.007)**	0.001 (0.013)	**−0.036** *** **(0.013)**	**−0.016** ** **(0.007)**	0.002 (0.003)
KIDS	0.020 (0.193)	**0.223** * **(0.129)**	**0.348** *** **(0.106)**	**0.383** *** (0.087)	**0.179** * **(0.108)**	**0.710** *** **(0.174)**	−0.001 (0.007)	**−0.023** ** **(0.011)**	**−0.038** *** **(0.013)**	−0.032 (0.021)	**0.075** *** **(0.020)**	0.005 (0.010)	**0.013** *** **(0.004)**
EDUC	0.030 (0.249)	0.139 (0.165)	0.098 (0.142)	0.170 (0.134)	−0.076 (0.175)	0.097 (0.358)	−0.001 (0.009)	−0.014 (0.016)	−0.002 (0.019)	−0.023 (0.031)	**0.049** * **(0.028)**	−0.010 (0.017)	0.002 (0.006)

Table 4. *Cont.*

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [ab]	**1, 2 vs. 3, 4, 5, 6, 7**	**1, 2, 3 vs. 4, 5, 6, 7**	**1, 2, 3, 4 vs. 5, 6, 7**	**1, 2, 3, 4, 5 vs. 6, 7**	**1, 2, 3, 4, 5, 6 vs. 7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
GENDER	0.014 (0.176)	**0.134** *** **(0.120)**	0.134 (0.102)	**−0.180** *** **(0.092)**	**−0.299** ** **(0.119)**	−0.069 (0.216)	−0.001 (0.007)	−0.014 (0.011)	−0.010 (0.013)	**0.068** *** **(0.021)**	−0.013 (0.021)	**−0.030** * **(0.012)**	−0.001 (0.004)
Constant	0.232 (0.705)	−1.438 (0.491)	**−2.115** *** **(0.415)**	**−4.255** *** **(0.381)**	**−5.973** *** **(0.500)**	**−9.888** *** **(0.959)**	-	-	-	-	-	-	-
Observation = 2641 Log likelihood = −4163.120													
Log likelihood ratio χ^2 (108) = 910.490 Pseudo R^2 = 0.099													

Notes: Bold font indicates significant coefficients with *, ** and *** denoting statistical significance at the 10%, 5% and 1% level, respectively; [a] 1 = extremely unlikely; 2 = very unlikely; 3 = moderately unlikely; 4 = neutral; 5 = moderately likely; 6 = very likely; 7 = extremely likely; [b] standard errors are in parentheses.

Table 5. Estimation results of generalized ordered linear logit model: California.

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [a,b]	**1, 2 vs. 3, 4, 5, 6, 7**	**1, 2, 3 vs. 4, 5, 6, 7**	**1, 2, 3, 4 vs. 5, 6, 7**	**1, 2, 3, 4, 5 vs. 6, 7**	**1, 2, 3, 4, 5, 6 vs. 7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
RATE	0.055 (0.185) [b]	**0.197** ** **(0.085)**	**0.175** * **(0.070)**	0.017 (0.062)	0.104 (0.086)	**0.553** ** **(0.214)**	−0.002 (0.005)	−0.016 (0.008)	−0.012 (0.009)	**0.025** * **(0.015)**	−0.007 (0.014)	0.007 (0.009)	**0.004** ** **(0.002)**
TURF	0.232 (0.176)	−0.124 (0.098)	−0.051 (0.082)	0.080 (0.071)	0.078 (0.104)	−0.274 (0.262)	−0.007 (0.005)	**0.018** ** **(0.008)**	−0.002 (0.010)	**−0.028** * **(0.016)**	0.011 (0.016)	0.010 (0.010)	−0.002 (0.002)
WATER	0.130 (0.162)	0.098 (0.097)	0.009 (0.079)	0.080 (0.071)	−0.082 (0.103)	0.208 (0.223)	−0.004 (0.005)	−0.005 (0.008)	0.007 (0.009)	−0.018 (0.016)	**0.028** * **(0.016)**	−0.010 (0.010)	0.002 (0.002)
SOIL	0.046 (0.192)	**0.158** * **(0.089)**	0.078 (0.070)	0.076 (0.063)	**0.156** * **(0.093)**	0.107 (0.239)	−0.001 (0.006)	−0.012 (0.008)	0.001 (0.009)	−0.005 (0.014)	0.002 (0.014)	**0.015** * **(0.009)**	0.001 (0.002)
SMS	**0.856** * **(0.483)**	**0.444** ** **(0.181)**	**0.337** *** **(0.126)**	**0.207** ** **(0.083)**	−0.076 (0.104)	−0.188 (0.246)	**−0.025** ** **(0.012)**	−0.014 (0.016)	−0.017 (0.017)	0.006 (0.023)	**0.058** *** **(0.018)**	−0.007 (0.010)	−0.001 (0.002)
ET	−0.588 (0.500)	−0.026 (0.205)	−0.077 (0.148)	−0.082 (0.097)	**0.267** ** **(0.114)**	0.14 (0.233)	0.017 (0.014)	−0.015 (0.018)	0.011 (0.019)	0.007 (0.027)	**−0.047** ** **(0.021)**	**0.027** ** **(0.012)**	0.001 (0.002)
CONSERVE	0.061 (0.163)	−0.159 (0.113)	0.049 (0.096)	0.138 (0.086)	**0.280** ** **(0.115)**	0.07 (0.246)	−0.002 (0.005)	**0.016** * **(0.008)**	**−0.022** * **(0.012)**	−0.025 (0.021)	0.004 (0.019)	**0.029** ** **(0.011)**	0.001 (0.002)

Table 5. *Cont.*

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [a,b]	1, 2 vs. 3, 4, 5, 6, 7	1, 2, 3 vs. 4, 5, 6, 7	1, 2, 3, 4 vs. 5, 6, 7	1, 2, 3, 4, 5 vs. 6, 7	1, 2, 3, 4, 5, 6 vs. 7	1	2	3	4	5	6	7
RESTRICT	−0.056 (0.111)	−0.038 (0.078)	−0.003 (0.066)	0.015 (0.062)	0.085 (0.091)	0.777 *** (0.267)	0.002 (0.003)	0.002 (0.006)	−0.003 (0.008)	−0.004 (0.014)	−0.005 (0.014)	0.003 (0.009)	0.006 ** (0.002)
NEIGH	0.120 (0.137)	0.067 (0.088)	0.051 (0.074)	0.136 ** (0.066)	0.144 (0.088)	−0.313 (0.198)	−0.003 (0.004)	−0.002 (0.007)	−0.003 (0.009)	−0.024 (0.016)	0.018 (0.014)	0.017 ** (0.009)	−0.002 (0.002)
STATE	0.143 (0.193)	0.145 (0.141)	0.111 (0.115)	−0.087 (0.110)	−0.227 (0.147)	−0.670 ** (0.268)	−0.004 (0.006)	−0.009 (0.010)	−0.006 (0.016)	0.040 (0.024)	0.002 (0.026)	−0.019 (0.015)	−0.005 ** (0.002)
PRICE	0.150 (0.095)	0.302 *** (0.072)	0.236 *** (0.057)	0.163 *** (0.050)	0.167 ** (0.070)	0.186 (0.147)	−0.004 (0.003)	−0.022 *** (0.005)	−0.013 * (0.008)	0.000 (0.012)	0.022 * (0.011)	0.016 ** (0.007)	0.001 (0.001)
EASE	0.024 (0.105)	0.057 (0.078)	0.082 (0.062)	0.118 ** (0.059)	0.129 (0.087)	0.231 (0.212)	−0.001 (0.003)	−0.004 (0.006)	−0.009 (0.009)	−0.015 (0.013)	0.015 (0.013)	0.012 (0.009)	0.002 (0.002)
RELIABLE	0.155 (0.115)	0.108 (0.084)	−0.030 (0.069)	0.083 (0.064)	0.174 * (0.090)	0.407 * (0.225)	−0.004 (0.003)	−0.005 (0.006)	0.014 (0.009)	−0.025 * (0.015)	0.002 (0.014)	0.015 * (0.009)	0.003 * (0.002)
INCOME	0.229 * (0.127)	0.176 ** (0.086)	0.107 * (0.065)	0.175 *** (0.056)	0.167 ** (0.078)	0.144 (0.196)	−0.007 * (0.004)	−0.009 (0.006)	−0.002 (0.009)	−0.025 * (0.013)	0.025 ** (0.013)	0.016 ** (0.008)	0.001 (0.001)
AGE	−0.814 *** (0.207)	−0.290 ** (0.133)	−0.306 *** (0.108)	−0.173 * (0.097)	0.040 (0.129)	0.369 (0.299)	0.024 *** (0.007)	0.002 (0.010)	0.026 * (0.014)	−0.009 (0.023)	−0.046 ** (0.021)	0.002 (0.013)	0.003 (0.002)
KIDS	0.004 (0.429)	0.394 (0.272)	0.678 *** (0.210)	0.581 *** (0.154)	0.242 (0.191)	0.35 (0.419)	0.000 (0.012)	−0.034 * (0.020)	−0.079 *** (0.027)	−0.028 (0.039)	0.116 *** (0.036)	0.023 (0.019)	0.003 (0.003)
EDUC	−0.431 (0.509)	−0.002 (0.303)	0.257 (0.256)	0.178 (0.238)	−0.015 (0.311)	0.685 (0.888)	0.011 (0.011)	−0.011 (0.024)	−0.045 (0.036)	0.003 (0.057)	0.044 (0.049)	−0.005 (0.032)	0.004 (0.004)
GENDER	−0.406 (0.342)	0.113 (0.220)	0.327 * (0.184)	−0.023 (0.161)	−0.322 (0.209)	0.880 * (0.472)	0.011 (0.010)	−0.021 (0.017)	−0.046 * (0.024)	0.061 (0.038)	0.029 (0.035)	−0.040 * (0.023)	0.006 * (0.003)
Constant	0.853 (1.366)	−2.074 ** (0.940)	−2.597 *** (0.783)	−4.594 *** (0.714)	−6.694 *** (0.969)	−12.219 *** (2.195)	-	-	-	-	-	-	-

Observation = 873
Log likelihood = −1303.323
Log likelihood ratio χ^2 (108) = 416.710
Pseudo R^2 = 0.138

Notes: Bold font indicates significant coefficients with *, ** and *** denoting statistical significance at the 10%, 5% and 1% level, respectively; [a] 1 = extremely unlikely; 2 = very unlikely; 3 = moderately unlikely; 4 = neutral; 5 = moderately likely; 6 = very likely; 7 = extremely likely; [b] standard errors are in parentheses.

Table 6. Estimation results of generalized ordered linear logit model: Florida.

	Thresholds between Purchase Likelihood						**Marginal Effects on Purchase Likelihood**						
	1 vs. 2, 3, 4, 5, 6, 7 [ab]	**1, 2 vs. 3, 4, 5, 6, 7**	**1, 2, 3 vs. 4, 5, 6, 7**	**1, 2, 3, 4 vs. 5, 6, 7**	**1, 2, 3, 4, 5 vs. 6, 7**	**1, 2, 3, 4, 5, 6 vs. 7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
RATE	0.209	**0.153** *	0.059	**0.159** ***	**0.192** **	0.141	−0.005	−0.011	0.005	**−0.028** **	0.018	**0.018** **	0.003
	(0.128)	**(0.086)**	(0.070)	**(0.062)**	**(0.079)**	(0.151)	(0.003)	(0.008)	(0.010)	**(0.014)**	(0.014)	**(0.008)**	(0.003)
TURF	0.174	0.002	−0.052	**−0.133** *	−0.090	−0.183	−0.004	0.004	0.010	0.023	−0.023	−0.006	−0.004
	(0.159)	(0.097)	(0.082)	**(0.076)**	(0.100)	(0.168)	(0.004)	(0.010)	(0.011)	(0.017)	(0.017)	(0.010)	(0.003)
WATER	−0.222	−0.059	0.028	**0.177** **	0.165	0.202	0.005	0.001	−0.011	**−0.038** **	0.026	0.014	0.004
	(0.170)	(0.101)	(0.090)	**(0.081)**	(0.104)	(0.197)	(0.004)	(0.010)	(0.011)	**(0.019)**	(0.018)	(0.010)	(0.004)
SOIL	0.038	**0.214** **	0.154	0.040	0.077	0.003	−0.001	**−0.022** **	−0.006	0.019	0.001	0.008	0.000
	(0.132)	**(0.090)**	(0.074)	(0.065)	(0.083)	(0.185)	(0.003)	**(0.009)**	(0.011)	(0.015)	(0.014)	(0.009)	(0.004)
SMS	0.150	0.096	0.176	0.129	**0.201** *	0.125	−0.004	−0.006	−0.022	0.001	0.010	**0.019** *	0.002
	(0.180)	(0.139)	(0.120)	(0.096)	**(0.107)**	(0.213)	(0.004)	(0.012)	(0.018)	(0.025)	(0.021)	**(0.011)**	(0.004)
ET	**0.704** **	**0.306** *	0.149	0.039	−0.059	−0.082	**−0.017** **	−0.015	0.005	0.018	0.016	−0.005	−0.002
	(0.337)	**(0.177)**	(0.141)	(0.108)	(0.117)	(0.224)	**(0.007)**	(0.016)	(0.021)	(0.029)	(0.024)	(0.012)	(0.004)
CONSERVE	0.048	0.080	**0.184** **	**0.173** **	0.082	**0.583** ***	−0.001	−0.007	**−0.026** **	−0.008	**0.034** **	−0.002	**0.011** **
	(0.165)	(0.102)	**(0.083)**	**(0.076)**	(0.096)	**(0.224)**	(0.004)	(0.009)	**(0.012)**	(0.017)	**(0.016)**	(0.010)	**(0.005)**
RESTRICT	0.007	−0.003	−0.004	**−0.109** *	−0.002	−0.057	0.000	0.000	0.000	**0.026** *	**−0.027** *	0.001	−0.001
	(0.142)	(0.083)	(0.069)	**(0.064)**	(0.084)	(0.149)	(0.003)	(0.008)	(0.010)	**(0.015)**	**(0.015)**	(0.008)	(0.003)
NEIGH	0.012	0.001	0.044	**0.147** **	0.058	0.150	0.000	0.000	−0.008	**−0.028** *	**0.030** **	0.003	0.003
	(0.116)	(0.080)	(0.069)	**(0.065)**	(0.085)	(0.160)	(0.003)	(0.007)	(0.010)	**(0.015)**	**(0.015)**	(0.008)	(0.003)
STATE	0.206	0.007	−0.086	0.095	0.112	−0.226	−0.005	0.004	0.017	**−0.039** *	0.011	0.017	−0.004
	(0.176)	(0.117)	(0.100)	(0.095)	(0.124)	(0.206)	(0.004)	(0.011)	(0.014)	**(0.022)**	(0.022)	(0.012)	(0.004)
PRICE	**0.229** **	**0.177** ***	**0.198** ***	**0.118** ***	**0.201** ***	**0.227** *	**−0.006** **	**−0.013** **	**−0.018** **	0.008	0.007	**0.017** ***	0.004
	(0.099)	**(0.061)**	**(0.050)**	**(0.045)**	**(0.061)**	**(0.130)**	**(0.003)**	**(0.006)**	**(0.007)**	(0.010)	(0.010)	**(0.006)**	(0.003)
EASE	0.136	0.001	0.015	0.053	0.047	0.155	−0.003	0.003	−0.003	−0.010	0.008	0.002	0.003
	(0.121)	(0.064)	(0.054)	(0.053)	(0.079)	(0.183)	(0.003)	(0.006)	(0.007)	(0.011)	(0.012)	(0.008)	(0.004)
RELIABLE	0.061	**0.126** *	**0.140** **	**0.126** **	**0.193** **	0.179	−0.001	**−0.012** *	**−0.013** **	−0.005	0.010	**0.017** **	0.003
	(0.119)	**(0.066)**	**(0.057)**	**(0.057)**	**(0.084)**	(0.177)	(0.003)	**(0.006)**	**(0.008)**	(0.012)	(0.013)	**(0.008)**	(0.003)
INCOME	**0.291** **	0.118	0.103	**0.137** **	0.049	0.137	**−0.007** *	−0.005	−0.007	−0.015	**0.028** *	0.003	0.003
	(0.142)	(0.093)	(0.074)	**(0.069)**	(0.094)	(0.173)	**(0.004)**	(0.009)	(0.011)	(0.015)	**(0.016)**	(0.009)	(0.003)
AGE	**−0.733** ***	**−0.360** ***	**−0.385** ***	**−0.271** ***	−0.137	0.200	**0.018** ***	**0.020** *	**0.033** ***	−0.005	**−0.052** **	−0.019	0.004
	(0.227)	**(0.121)**	**(0.105)**	**(0.098)**	(0.134)	(0.274)	**(0.006)**	**(0.012)**	**(0.014)**	(0.022)	**(0.023)**	(0.014)	(0.005)
KIDS	−0.527	0.109	0.126	0.216	0.199	**0.942** ***	0.013	−0.024	−0.012	−0.030	0.032	0.003	**0.018** ***
	(0.394)	(0.229)	(0.182)	(0.152)	(0.187)	**(0.320)**	(0.009)	(0.021)	(0.025)	(0.036)	(0.034)	(0.018)	**(0.007)**
EDUC	−0.107	0.182	0.078	0.150	0.118	−0.240	0.002	−0.023	0.006	−0.022	0.024	0.018	−0.005
	(0.463)	(0.286)	(0.234)	(0.226)	(0.319)	(0.631)	(0.010)	(0.030)	(0.036)	(0.050)	(0.049)	(0.030)	(0.015)

Table 6. *Cont.*

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [ab]	**1, 2 vs. 3, 4, 5, 6, 7**	**1, 2, 3 vs. 4, 5, 6, 7**	**1, 2, 3, 4 vs. 5, 6, 7**	**1, 2, 3, 4, 5 vs. 6, 7**	**1, 2, 3, 4, 5, 6 vs. 7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
GENDER	**0.607** *	0.323	0.263	−0.066	**−0.429** **	−0.58	−0.016	−0.019	−0.014	**0.066** *	0.033	−0.036	−0.012
	(0.355)	(0.212)	(0.173)	(0.161)	**(0.210)**	(0.405)	(0.010)	(0.021)	(0.025)	**(0.035)**	(0.036)	(0.023)	(0.010)
Constant	0.252	−1.149	**−1.614** **	**−3.764** ***	**−6.070** ***	**−9.970** ***	-	-	-	-	-	-	-
	(1.323)	(0.838)	**(0.680)**	**(0.627)**	**(0.843)**	**(1.831)**							
Observation = 881													
Log likelihood = −1391.790													
Log likelihood ratio χ^2 (108) = 335.730													
Pseudo R^2 = 0.108													

Notes: Bold font indicates significant coefficients with *, ** and *** denoting statistical significance at the 10%, 5% and 1% level, respectively; [a] 1 = extremely unlikely; 2 = very unlikely; 3 = moderately unlikely; 4 = neutral; 5 = moderately likely; 6 = very likely; 7 = extremely likely; [b] standard errors are in parentheses.

Table 7. Estimation results of generalized ordered linear logit model: Texas.

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [ab]	**1, 2 vs. 3, 4, 5, 6, 7**	**1, 2, 3 vs. 4, 5, 6, 7**	**1, 2, 3, 4 vs. 5, 6, 7**	**1, 2, 3, 4, 5 vs. 6, 7**	**1, 2, 3, 4, 5, 6 vs. 7**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
RATE	0.095	0.066	0.034	0.046	**0.169** **	**0.334** *	−0.004	−0.004	0.001	−0.005	−0.002	0.008	**0.005** *
	(0.118)	(0.076)	(0.064)	(0.058)	**(0.081)**	**(0.172)**	(0.005)	(0.008)	(0.009)	(0.014)	(0.013)	(0.006)	**(0.003)**
TURF	**−0.280** **	0.102	0.015	**0.132** *	**0.257** **	**0.839** ***	**0.011** **	**−0.022** **	0.009	**−0.029** *	0.012	0.008	**0.012** ***
	(0.127)	(0.093)	(0.079)	**(0.074)**	**(0.107)**	**(0.248)**	**(0.005)**	**(0.009)**	(0.011)	**(0.017)**	(0.017)	(0.008)	**(0.004)**
WATER	0.121	0.106	−0.006	−0.041	−0.140	−0.304	−0.005	−0.007	0.013	0.009	0.001	−0.007	−0.005
	(0.141)	(0.101)	(0.083)	(0.078)	(0.115)	(0.216)	(0.005)	(0.009)	(0.012)	(0.018)	(0.018)	(0.009)	(0.004)
SOIL	0.098	0.023	**0.173** **	0.092	**0.224** **	**−0.965** ***	−0.004	0.001	**−0.027** ***	0.008	0.005	**0.032** ***	**−0.014** ***
	(0.133)	(0.090)	**(0.073)**	(0.067)	**(0.099)**	**(0.242)**	(0.005)	(0.008)	**(0.010)**	(0.015)	(0.015)	**(0.008)**	**(0.005)**
SMS	−0.006	0.193	**0.186** *	**0.202** **	0.129	**0.486** **	0.000	**−0.021** *	−0.011	−0.017	**0.039** *	0.003	**0.007** **
	(0.185)	(0.132)	**(0.106)**	**(0.091)**	(0.115)	**(0.227)**	(0.007)	**(0.012)**	(0.014)	(0.020)	**(0.021)**	(0.008)	**(0.003)**
ET	0.345	0.030	0.171	0.103	0.040	−0.213	−0.013	0.010	−0.026	0.004	0.022	0.006	−0.003
	(0.286)	(0.160)	(0.124)	(0.097)	(0.115)	(0.214)	(0.010)	(0.016)	(0.016)	(0.023)	(0.022)	(0.008)	(0.003)
CONSERVE	0.261	0.027	0.047	0.121	−0.085	**0.659** ***	−0.010	0.007	−0.005	−0.021	**0.036** *	**−0.017** **	**0.010** **
	(0.173)	(0.106)	(0.092)	(0.083)	(0.106)	**(0.237)**	(0.007)	(0.011)	(0.011)	(0.020)	**(0.019)**	**(0.008)**	**(0.004)**

Table 7. *Cont.*

	Thresholds between Purchase Likelihood						Marginal Effects on Purchase Likelihood						
	1 vs. 2, 3, 4, 5, 6, 7 [ab]	1, 2 vs. 3, 4, 5, 6, 7	1, 2, 3 vs. 4, 5, 6, 7	1, 2, 3, 4 vs. 5, 6, 7	1, 2, 3, 4, 5 vs. 6, 7	1, 2, 3, 4, 5, 6 vs. 7	1	2	3	4	5	6	7
RESTRICT	0.247 ** (0.120)	0.036 (0.081)	0.000 (0.069)	0.056 (0.064)	0.018 (0.090)	0.307 * (0.179)	−0.009 ** (0.005)	0.005 (0.008)	0.004 (0.009)	−0.014 (0.015)	0.012 (0.015)	−0.003 (0.007)	0.005 (0.003)
NEIGH	−0.318 ** (0.145)	0.076 (0.092)	0.188 ** (0.075)	0.131 * (0.069)	0.131 (0.094)	0.675 *** (0.185)	0.012 ** (0.006)	−0.020 ** (0.009)	−0.024 ** (0.011)	0.000 (0.016)	0.021 (0.016)	0.000 (0.007)	0.010 *** (0.004)
STATE	−0.513 ** (0.239)	−0.240 * (0.134)	−0.280 ** (0.118)	−0.174 * (0.105)	−0.248 ** (0.124)	−0.748 *** (0.250)	0.019 ** (0.009)	0.007 (0.013)	0.022 (0.014)	−0.006 (0.026)	−0.023 (0.023)	−0.008 (0.010)	−0.011 ** (0.004)
PRICE	0.079 (0.106)	0.126 * (0.067)	0.153 *** (0.055)	0.059 (0.048)	0.062 (0.065)	0.001 (0.128)	−0.003 (0.004)	−0.011 * (0.006)	−0.012 * (0.007)	0.012 (0.011)	0.009 (0.011)	0.005 (0.005)	0.000 (0.002)
EASE	0.246 ** (0.104)	0.149 ** (0.074)	0.154 ** (0.067)	0.158 ** (0.065)	0.231 ** (0.091)	0.494 *** (0.169)	−0.009 ** (0.004)	−0.007 (0.007)	−0.010 (0.009)	−0.012 (0.015)	0.020 (0.015)	0.011 (0.007)	0.007 *** (0.003)
RELIABLE	0.110 (0.108)	0.228 *** (0.078)	0.160 ** (0.067)	0.322 *** (0.064)	0.270 ** (0.088)	0.190 (0.139)	−0.004 (0.004)	−0.021 *** (0.007)	−0.002 (0.009)	−0.051 *** (0.015)	0.057 *** (0.014)	0.019 *** (0.006)	0.003 (0.002)
INCOME	0.468 *** (0.128)	0.046 (0.068)	0.050 (0.060)	0.002 (0.056)	0.085 (0.081)	−0.147 (0.154)	−0.018 *** (0.005)	0.013 * (0.007)	−0.003 (0.007)	0.008 (0.013)	−0.006 (0.013)	0.009 (0.006)	−0.002 (0.002)
AGE	−0.327 * (0.178)	−0.225 * (0.125)	−0.167 (0.109)	−0.170 (0.105)	−0.267 * (0.147)	0.330 (0.332)	0.012 * (0.007)	0.012 (0.011)	0.004 (0.013)	0.012 (0.025)	−0.020 (0.024)	−0.026 ** (0.011)	0.005 (0.005)
KIDS	0.004 (0.329)	0.074 (0.224)	0.324 * (0.187)	0.415 *** (0.159)	0.245 (0.205)	0.926 ** (0.377)	0.000 (0.012)	−0.008 (0.020)	−0.048 ** (0.023)	−0.045 (0.038)	0.081 ** (0.037)	0.006 (0.015)	0.014 ** (0.007)
EDUC	1.028 ** (0.453)	0.345 (0.333)	−0.125 (0.283)	0.114 (0.256)	−0.145 (0.322)	0.621 (0.713)	−0.057 (0.036)	0.015 (0.038)	0.063 * (0.037)	−0.048 (0.061)	0.039 (0.055)	−0.019 (0.027)	0.007 (0.007)
GENDER	−0.415 (0.347)	−0.062 (0.222)	0.014 (0.186)	−0.437 *** (0.165)	−0.177 (0.219)	0.865 * (0.469)	0.015 (0.012)	−0.008 (0.021)	−0.009 (0.024)	0.109 *** (0.039)	−0.092 ** (0.037)	−0.026 (0.017)	0.012 * (0.007)
Constant	0.687 (1.424)	−1.146 (0.931)	−1.771 ** (0.772)	−4.448 *** (0.705)	−5.775 *** (0.948)	−12.903 *** (2.140)	-	-	-	-	-	-	-
Observation = 887 Log likelihood = −1308.848 Log likelihood ratio χ^2 (108) = 466.650 Pseudo R^2 = 0.151													

Notes: Bold font indicates significant coefficients with *, ** and *** denoting statistical significance at the 10%, 5% and 1% level, respectively; [a] 1 = extremely unlikely; 2 = very unlikely; 3 = moderately unlikely; 4 = neutral; 5 = moderately likely; 6 = very likely; 7 = extremely likely; [b] standard errors are in parentheses.

3.1. Knowledge and Smart Irrigation

Cumulatively, marginal effect estimates support the first hypothesis (H1) that higher knowledge levels are associated with increased purchase likelihood (Table 4). Respondents' knowledge levels of sprinkler application rates and soil types are positively correlated with purchase likelihood for smart irrigation controllers. Specifically, higher knowledge about sprinkler system irrigation rates reduces the probability of selecting "very unlikely" to purchase smart irrigation controllers by 1.1%, while increasing the probability of selecting "very/extremely likely" to purchase the controllers by 1.1% and 0.4%, respectively. Furthermore, soil type-related knowledge increases smart irrigation controller purchase likelihood, while reducing the probability of respondents' selecting "very unlikely" and "moderately unlikely" by 1.0% and 1.1%, respectively. Higher levels of knowledge for sprinkler systems increases the probability of choosing "very likely" to purchase by 1.5%.

The differences in knowledge and purchase likelihood between the three states (in support of Hypothesis 6) are also evaluated in Tables 5–7. Marginal effect estimates for California indicate that sprinkler application rate knowledge increases the probability of selecting "extremely likely" to purchase the controllers by 0.4% (Table 5). Similarly, respondents' knowledge about water needs of turfgrass and plants increases the "moderate" purchase likelihood by 2.8%. Knowledge about soil type also increases the probability of "very likely" purchasing the controllers by 1.5%. Respondents from Florida and Texas exhibit slightly different results, with respondents having an increased probability (1.8% for Florida, 0.5% for Texas) of purchasing smart irrigation controllers if they are knowledgeable about sprinkler application rates (Tables 6 and 7). The probability of Florida respondent's selecting "very unlikely" to purchase decrease by 2.2% if they are knowledgeable about soil type. Interestingly, Texas respondents' knowledge about soil type reduces the probability of "extremely likely" to purchase by 1.4% while increasing the probability of "very likely" to purchase by 3.2%. In addition, knowledge about lawns and landscape is associated with the purchase likelihood, but the marginal effects vary across the states (H6). An increased knowledge level tends to increase the purchase likelihood, showing that homeowners utilize their understanding of the unique characteristics of their lawns/landscapes when determining their purchase likelihood of smart irrigation controllers.

Smart irrigation controller knowledge-related results support Hypothesis 2 (Tables 4–7). In the full sample, greater SMS and ET controller knowledge is associated with higher purchase likelihood. Greater SMS controller knowledge reduces the probability of "very/moderately unlikely" to purchase smart irrigation controllers by 1.4% and 1.8%, respectively. Additionally, it increases the "moderately likely" to purchase probability by 3.2%. In addition, greater ET controller knowledge reduces the probability of "extremely unlikely" to purchase by 0.9%, whereas it increases the "very likely" purchasing probability by 1.0%.

When comparing the different states, in general, greater knowledge levels about the SMS and ET controllers are associated with higher purchase likelihood, but their relevance varies across the states, supporting Hypothesis 6 (Tables 5–7). In California, higher SMS controller knowledge reduces the probability of selecting "extremely unlikely" to purchase smart irrigation controllers by 2.5%, but it increases the "moderately likely" to purchase probability by 5.8% (Table 5). Conversely, greater knowledge about the ET controller decreases the probability of "moderately likely" to purchase smart irrigation controllers, while increasing the probability of being "very likely" to purchase them. For Florida homeowners, greater knowledge about SMS controllers increases the probability of being "very likely" to purchase by 1.9%, whereas greater knowledge about ET controllers decreases the probability of "extremely unlikely" to purchase by 1.7% (Table 6). Similarly, in Texas, more SMS controller knowledge reduces their probability of "very unlikely" to purchase smart irrigation controllers by 2.1%; however, it increases their probability of "moderately/extremely likely" to purchase a smart controller by 3.9% and 0.7%, respectively (Table 7). Overall, across the states, homeowners' SMS and ET controller knowledge positively influences their likelihood of purchasing smart irrigation controllers. Knowledge about the SMS controller, in particular, is more relevant to their purchase likelihood than the ET controller knowledge.

3.2. Perceptions, Smart Irrigation, and Demographics

The results in Table 4 support Hypothesis 3 that higher water-related perceptions increase homeowners' smart irrigation controller purchase likelihood. Overall, homeowners with positive perceptions about water conservation, who are aware of regional water restrictions and believe their neighbors over-irrigate are more likely to purchase smart irrigation controllers. Specifically, homeowners with perceptions that their water conservation efforts affect the total supply lower their probability of "moderately unlikely" to purchase smart irrigation controllers by 1.7% while increasing the probability of selecting "moderately likely" and "extremely likely" to purchase by 2.8% and 0.6%, respectively. Homeowners with greater awareness of their area's water restrictions are 0.4% more probable to select "extremely likely" to purchase smart irrigation controllers. Regarding neighbor effects, homeowners with perceptions that their neighbors over-irrigating have an increased probability of selecting "moderately/very likely" to purchase smart irrigation controllers by 2.0% and 0.8%, respectively. Perceptions that there are insufficient state water resources reduces homeowners' "extremely likely" rating to purchase smart irrigation technology by 0.7%. Overall, these results indicate that homeowners are aware of the need for water conservation and local water-usage restrictions, but they question if there are insufficient water resources within their state.

Since different states have various environmental conditions that contribute to water needs (i.e., drought, temperature, rainfall, etc.), we assessed consumer perceptions by state. Overall, homeowners' perceptions about water availability are positively associated with their purchase likelihood, but variations occur across the states (Tables 5–7). If California homeowners' reported a higher level of agreement with the statements on water conservation and neighbors over-irrigating, the homeowners had an increased probability of "very likely" purchasing smart irrigation controllers by 2.9% and 1.7%, respectively (Table 5). California homeowners' perception about water restrictions raised the probability of "extremely likely" purchasing smart irrigation controllers by 0.6%. However, their perceptions about the state's water resources reduces the probability of selecting "extremely likely" to purchase by 0.5%. In Table 6, the marginal effects of Florida homeowners' water conservation perceptions also increases the probability of "moderately/extremely likely" purchasing smart irrigation controllers by 3.4% and 1.1%. Their perceptions about neighbors' over-irrigation increases the probability of "moderately likely" to purchase them by 3.0%, but the purchase probability decreases if the homeowner had perceptions about water restrictions in their area (2.7%). Lastly, for Texas homeowners, Table 7 shows that water conservation perceptions had mixed results. Homeowners with water conservation beliefs have an increased probability of being "moderately likely" and "extremely likely" to purchase (3.6% and 1.0%, respectively), but a reduced probability of being "very likely" to purchase smart irrigation controllers (1.7%). In addition, a higher perception that their neighbors over-irrigate increases the extremely likely purchase probability by 1.0%, whereas it decreases the "moderately unlikely/very unlikely" purchasing probabilities by 2.0% and 2.4%, respectively. Statewide water availability results indicate that Texas homeowners with this perception are less likely to purchase smart irrigation controllers.

Respondents' perceptions about smart irrigation controllers relative to conventional irrigation controllers are positively associated with their purchase likelihood, supporting Hypothesis 4. In Table 4, purchase likelihood increases when homeowners perceive smart irrigation controllers as more advantageous (i.e., better priced, ease of use and reliable) than conventional irrigation controllers. The probability of selecting "moderately likely", "very likely" and "extremely likely" to purchase categories increases by 1.2%, 1.2% and 0.3%, respectively, when homeowners perceived smart irrigation controllers as better priced. Unsurprisingly, the same three categories (moderate, very and extremely likely) to purchase conventional irrigation controllers decrease when homeowners perceive conventional irrigation controllers as better priced. Homeowners who perceive smart irrigation controllers as easy to use have an increased probability of selecting "moderately/extremely" likely to purchase (1.4% and 0.5%, respectively). Perceptions about the reliability of the controllers also are significant predictors of purchase likelihood. While higher perceptions about the reliability of conventional irrigation controllers decreases the probability of "extremely/very unlikely" to purchase smart irrigation controllers by 0.4% and 1.2%, a higher reliability perception for smart irrigation controllers increases the "moderately/very/extremely likely" to purchase by 2.4%, 1.9%, and 0.4%, respectively. As the perceived reliability of smart irrigation controllers becomes greater than that of conventional irrigation controllers, homeowners are more willing to purchase smart irrigation controllers.

Across the states, perceptions about smart irrigation controllers relative to conventional irrigation controllers are also associated positively with purchase likelihood. In Table 5, California homeowners' better price perceptions about smart irrigation controllers increase the "moderately likely" (2.2%) and "very likely" (1.6%) to purchase probability, while decreasing the "moderately unlikely" (1.3%) and "very unlikely" (2.2%) to purchase probability. The perceptions on ease of use are not significant, but higher perceptions about reliability increase the "extremely/very likely" to purchase probability by 1.5% and 0.3%, respectively. For Florida homeowners, better price perceptions decrease the probability of "extremely/very/moderately unlikely" to purchase smart irrigation controllers by 1.8%, 1.3% and 0.6%, respectively (Table 6). Perceptions about ease of use are insignificant for Florida homeowners. Higher reliability perceptions increase the "very likely" (1.7%) to purchase probability, but decrease the "moderately/very unlikely" (1.3% and 1.2%) to purchase probability. For Texas homeowners, perceptions about price, ease of use and reliability are associated with purchase likelihood (Table 7). Better price perceptions reduce the "moderately unlikely" (1.2%) and "very unlikely" (1.1%) to purchase probability. A higher ease of use perception reduces the "extremely unlikely" purchasing probability (0.9%) while raising the "extremely likely" to purchase probability (0.7%). In addition, higher reliability perceptions decrease the probability of "very unlikely" to purchase smart irrigation controllers (2.1%) and increase the "moderately/very likely" to purchase by 5.7% and 1.9%, respectively.

Finally, socio-demographic variables influence homeowners' likelihood of purchasing smart irrigation controllers, supporting Hypothesis 5. Older homeowners are less likely to purchase smart irrigation controllers (Table 4). Homeowners with higher incomes, more children or higher education levels are more likely to purchase smart irrigation controllers. Female homeowners are less likely to purchase smart irrigation controllers than male homeowners. The socio-demographic characteristics are also relevant to the purchase likelihood across the states. In particular, younger homeowners or those who have higher incomes, more children or higher education levels were more likely to purchase smart irrigation controllers (Tables 5–7).

4. Conclusions

As water scarcity becomes an increasingly important environmental issue, understanding consumer adoption and interest in water-efficient technologies is essential when determining the best policies, regulations and marketing/promotional strategies to encourage consumers to implement these products. In an effort to contribute to water conservation efforts in urban environments (where areas devoted to heavily maintained landscapes rapidly expand), irrigation equipment manufacturers and service providers offer "smart" irrigation controllers to environmentally-conscious homeowners. In contrast to conventional irrigation equipment, smart controller-based systems reduce water waste using sensors to regulate irrigation based on plant/turfgrass needs. While previous studies investigated human dimensions in water conservation practices, many focus on practices within households by linking individuals' environmental attitudes [25], characteristics of the dwelling [50], and home ownership [51] with the probability of the adoption of water-efficient household appliances. With technological advancements in the main household appliances (e.g., washing machine, dishwasher, shower and toilet), the adoption of such equipment is (relatively) not cost-prohibitive, as most modern appliances are manufactured to meet water-saving requirements/standards. However, factors that influence outdoor/landscape irrigation, which can represent the majority of water use (and waste), are still poorly understood. In an attempt to address this shortcoming in the literature, this paper used an online survey of California, Florida and Texas homeowners to determine how their knowledge, perceptions and demographics influence their probability of purchasing smart irrigation controllers.

The first contribution of this paper is centered on identifying the effects of knowledge about smart irrigation and purchase likelihood, and its implications for stakeholders involved in related policy decisions. Results based on responses from 2641 homeowners show that higher levels of knowledge (related to sprinkler application rates, soil type, SMS and ET controllers) positively influence their likelihood of switching to smart irrigation systems (H1, H2). Although differences exist across the states, the impact of sprinkler application rate-related knowledge is consistent, which indicates that consumers who are generally more knowledgeable about irrigation systems are more interested in purchasing smart irrigation technology. Additionally, homeowners' knowledge about SMS controllers consistently increased purchase likelihood. This suggests that SMS-based controllers are slightly preferred to the ET-based controllers. Future studies can evaluate this preference further, specifically focusing on the differences of SMS- and ET-based controllers. In general, results indicate that it is important to educate (and advertise to) homeowners about the characteristics of smart irrigation controllers, which will, in turn, contribute to an increase in their purchase likelihood.

The second contribution to the extant literature is that individuals' perceptions are found to influence purchase likelihood of smart irrigation systems. Homeowners' perceptions about conservation efforts, water restrictions, and their neighbors' irrigation habits increase purchase likelihood (H3). Regardless of state, homeowners' beliefs that water conservation efforts directly influence overall water supply positively influence their purchase likelihood of a smart irrigation system. Additionally, homeowners' purchase likelihood increases if they perceived smart irrigation controllers as better priced, easier to use, or more reliable when compared to conventional irrigation systems (H4). State-level differences indicate that perceptions about the reliability (as opposed to price or ease of use) of smart systems are the most influential. Policy makers and educators can utilize this information to influence consumer behavior and promote installation/use of smart irrigation systems.

Finally, our results demonstrate that several socio-demographic variables influence homeowners' purchase likelihood for smart irrigation controllers (H5). Specifically, younger homeowners, having children (under 18 years old), a higher level of education, being male, or those with higher incomes are more likely to purchase smart irrigation controllers. The larger households and higher income results are consistent with other studies investigating the adoption of water-efficient appliances indicating the robustness of results [19,25]. Lastly, it is important to note that differences exist across the states with regards to knowledge, perceptions and demographics (supporting H6; Tables 5–7), likely due to state-specific water availability concerns and climatic differences.

In addition to the contributions of this paper, there are several limitations that are worth mentioning. Although the sample size was considerably large and the survey was conducted in states with large populations (representing one third of the U.S. total population) and water quantity/quality issues, our estimations are based on hypothetical questions (i.e., stated preference data). Further, the target respondents in our survey are only residents living in single-family homes with lawn and automated (but not smart) irrigation systems. Thus, the screening questions excluded households that (at the time of the survey) did not have automated irrigation, but could be potential adapters of smart irrigation systems in the future.

Acknowledgments: This research was supported by the Center for Landscape Conservation and Ecology at the University of Florida and the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2014S1A3A2044459).

Author Contributions: Dong Hee Suh contributed to the development of the conceptual framework, analyzed the data and wrote the manuscript. Alicia Rihn assisted with data analysis and manuscript writing. Michael Dukes assisted with the conceptual framework and survey instrument development. Hayk Khachatryan developed the conceptual framework, designed the choice experiment, developed the survey instrument, conducted the survey, and assisted with data analysis and manuscript writing.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. St. Hilaire, R.; Arnold, M.A.; Wilkerson, D.C.; Devitt, D.A.; Hurd, B.H.; Lesikar, B.J.; Lohr, V.I.; Martin, C.A.; McDonald, G.V.; Morris, R.L.; et al. Efficient water use in residential urban landscapes. *HortScience* **2008**, *43*, 2081–2092.
2. Yue, C.; Hugie, K.; Watkins, E. Are consumers willing to pay more for low-input turfgrasses on residential lawns? Evidence from choice experiments. *J. Agric. Appl. Econ.* **2012**, *44*, 549–560. [CrossRef]
3. Donnelly, K.; Cooley, H. *Water Use Trends in the United States*; Pacific Institution: Oakland, CA, USA, 2015.
4. Brehm, J.M.; Pasko, D.K.; Eisenhauer, B.W. Identifying key factors in homeowner's adoption of water quality bet management practices. *Environ. Manag.* **2013**, *52*, 113–122. [CrossRef] [PubMed]
5. Shober, A.L.; Denny, G.C.; Broschat, T.K. Management of fertilizers and water for ornamental plants in urban landscapes: Current practices and impacts on water resources in Florida. *HortTechnology* **2010**, *20*, 94–106.
6. United States Environmental Protection Agency(EPA). WaterSense an EPA Partnership Program. 2016. Available online: https://www3.epa.gov/watersense/ (accessed on 14 July 2016).
7. Beard, J.B.; Green, R.L. The role of turfgrasses in environmental protection and their benefits to humans. *J. Environ. Qual.* **1994**, *23*, 452–460. [CrossRef]
8. Brethour, C.; Watson, G.; Sparling, B.; Bucknell, D.; Moore, T.-L. *Literature Review of Documented Health and Environmental Benefits Derived from Ornamental Horticulture Products*; Agriculture and Agri-Food Canada Markets and Trade: Ottawa, ON, Canada, 2007.
9. Hall, C.R.; Dickson, M.W. Economic, environmental, and health/well-being benefits associated with green industry products and services: A review. *J. Environ. Hortic.* **2011**, *29*, 96–103.
10. Qian, Y.; Follett, R.; Kimble, J. Soil organic carbon input from urban turfgrasses. *Soil Sci. Soc. Am. J.* **2010**, *74*, 366–371. [CrossRef]
11. Stier, J.C.; Steinke, K.; Ervin, E.H.; MHigginson, F.R.; McMaugh, P.E. Turfgrass benefits and issues. *Turfgrass Biol. Use Manag. Agron. Monogr.* **2013**, *56*, 105–145.
12. Badruzzaman, M.; Pinzon, J.; Oppenheimer, J.; Jacangelo, J.G. Sources of nutrients impacting surface waters in Florida: A review. *J. Environ. Manag.* **2012**, *109*, 80–92. [CrossRef] [PubMed]
13. Kaushal, S.S.; Groffman, P.M.; Band, L.E.; Elliott, E.M.; Shield, C.A.; Kendall, C. Tracking nonpoint source nitrogen pollution in human-impacted watersheds. *Environ. Sci. Technol.* **2011**, *45*, 8225–8232. [CrossRef] [PubMed]
14. Willis, R.M.; Stewart, R.A.; Giurco, D.P.; Talebpour, M.R.; Mousavinejad, A. End use water consumption in households: Impact of socio-demographic factors and efficient devices. *J. Clean. Prod.* **2013**, *60*, 107–115. [CrossRef]
15. Dukes, M.D.; Haley, M.B. Evaluation of Soil Moisture-Based on-Demand Irrigation Controllers, Phase II—Final Report. Southwest Florida Water Management District. 2009. Available online: http://abe.ufl.edu/mdukes/pdf/publications/SMS/SMS%20Phase%20II%20Final%20Report%2012-17-09.pdf (accessed on 14 July 2016).
16. U.S. Drought Monitor. *Tabular Data Archive—Percent Area in, U.S. Drought Monitor Categories*; U.S. Drought Monitor: Lincoln, NE, USA, 2016.
17. Ahmad, S.; Prashar, D. Evaluating municipal water conservation policies using a dynamic simulation model. *Water Resour. Manag.* **2010**, *24*, 3371–3395. [CrossRef]
18. Jorgensen, B.; Graymore, M.; O'Toole, K. Household water use behavior: An integrated model. *J. Environ. Manag.* **2009**, *91*, 227–236. [CrossRef] [PubMed]
19. Nauges, C. *Greening Household Behaviour and Water*; OECD Environment Working Papers; Organisation for Economic Co-operation and Development (OECD): Paris, France, 2014; Volume 73.
20. Oregon State University. WaterWise Gardening. 2016. Available online: http://extension.oregonstate.edu/yamhill/eco-gardening/waterwise-gardening (accessed on 14 July 2016).
21. The Metropolitan Water District of Southern California. SoCal Water$mart | Residential Rebates, Sacramento, CA. 2016. Available online: http://socalwatersmart.com/?page_id=3007 (accessed on 14 July 2016).
22. United States Department of Agriculture (USDA). *Water Conservation*; USDA: Beltsville, MD, USA, 2016.
23. Williams, R. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata J.* **2006**, *6*, 58–82.

24. Lee, M.; Tansel, B.; Balbin, M. Urban sustainability incentives for residential water conservation: Adoption of multiple high efficiency appliances. *Water Resour. Manag.* **2013**, *27*, 2531–2540. [CrossRef]
25. Millock, K.; Nauges, C. Household adoption of water-efficient equipment: The role of socio-economic factors, environmental attitudes and policy. *Environ. Resour. Econ.* **2010**, *46*, 539–565. [CrossRef]
26. Renwick, M.E.; Green, R. Do residential water demand side management policies measure up? An analysis of eight California water agencies. *J. Environ. Econ. Manag.* **2000**, *40*, 37–55. [CrossRef]
27. Davis, S.L.; Dukes, M.D. Landscape irrigation with evapotranspiration controllers in a humid climate. *Am. Soc. Agric. Biol. Eng.* **2012**, *55*, 571–580.
28. Riley, M. The cutting edge of residential smart irrigation technology. *Calif. Landsc.* **2005**, *19*, 19–26.
29. Cárdenas-Lailhacar, B.; Dukes, M.D. Soil moisture sensor landscape irrigation controllers: A review of multi-study results and future implications. *Trans. Am. Soc. Agric. Biol. Eng.* **2012**, *55*, 581–590.
30. Dukes, M.D. Water conservation potential of landscape irrigation smart controllers. *Trans. Am. Soc. Agric. Biol. Eng.* **2012**, *55*, 563–569.
31. Mayer, P.; DeOreo, W.; Hayden, M.; Davis, R.; Caldwell, E.; Miller, T.; Bickel, P.J. Evaulation of California Weather-Based "Smart" Irrigation Controller Programs. California Department of Water Resources. 2009. Available online: http://ucanr.edu/sites/UrbanHort/files/99641.pdf (accessed on 14 July 2016).
32. Bennear, L.S.; Lee, J.M.; Taylor, L.O. Participation Incentives, Rebound Effects and the Cost-Effectiveness of Rebates for Water Efficient Appliances. Duke Environmental Economics Working Paper Series, Nicholas Institute for Environemental Policy Solutions. Available online: http://ssrn.com/abstract=197001 (accessed on 14 July 2016).
33. Willis, R.M.; Stewart, R.A.; Panuwatwanich, K.; Williams, P.R.; Hollingsworth, A.L. Quantifying the influence of environmental and water conservation attitudes on household end use water consumption. *J. Environ. Manag.* **2011**, *92*, 1996–2009. [CrossRef] [PubMed]
34. Ajzen, I. From intentions to actions: A theory of planned behavior. In *Action-Control: From Cognition to Behavior*; Kuhl, J., Beckmann, J., Eds.; Springer: Berlin/Heidelberg, Germany, 1985; pp. 1–39.
35. Ajzen, I. Attitudes, traits, and actions: Dispositional prediction of behavior in personality and social psychology. In *Advances in Experimental Social Psychology*; Berkowitz, L., Ed.; Academic Press: New York, NY, USA, 1987; Volume 20, pp. 1–63.
36. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
37. National Gardening Association. *2013 National Gardening Survey*; The National Gardening Association: Williston, VT, USA, 2013.
38. Byrne, P.J.; Toensmeyer, U.C.; German, C.L.; Muller, H.R. Analysis of consumer attitudes toward organic produce and purchase likelihood. *J. Food Distrib. Res.* **1991**, *22*, 49–62.
39. Cook, A.J.; Kerr, G.N.; Moore, K. Attitudes and intentions towards purchasing GM food. *J. Econ. Psychol.* **2002**, *23*, 557–572. [CrossRef]
40. Lewis, M.; Singh, V.; Fay, S. An empirical study of the impact of nonlinear shipping and handling fees on purchase incidence and expenditure decisions. *Mark. Sci.* **2006**, *25*, 51–64. [CrossRef]
41. Rihn, A.; Khachatryan, H.; Campbell, B.; Hall, C.; Behe, B. Consumer Preferences for Organic Production Methods and Origin Promotions on Ornamental Plants: Evidence From Eye-tracking Experiments. *Agric. Econ.* **2016**. [CrossRef]
42. Shor, M.; Oliver, R.L. Price discrimination through online couponing: Impact on likelihood of purchase and profitability. *J. Econ. Psychol.* **2006**, *27*, 423–440. [CrossRef]
43. Suh, D.H.; Khachatryan, H.; Guan, Z. Why do we adopt environmentally friendly lawn care? Evidence from do-it-yourself consumers. *Appl. Econ.* **2016**, *48*, 2550–2561. [CrossRef]
44. Sunderer, G.; Rössel, J. Morality or economic interest? the impact of moral motives and economic factors on the purchase of fair trade groceries. *Int. J. Consum. Stud.* **2012**, *36*, 244–250. [CrossRef]
45. Greene, W.H. *Econometric Analysis*, 5th ed.; Prentice Hall: New York, NY, USA, 2003.
46. Train, K. *Discrete Choice Methods with Simulation*; Cambridge University Press: Cambridge, MA, USA, 2003.
47. Fu, V.K. Estimating generalized ordered logit models. *Stata Tech. Bull.* **1998**, *8*, 27–30.
48. Peterson, B.; Harrell, F.E. Partial proportional odds models for ordinal response variables. *Appl. Stat.* **1990**, *39*, 205–217. [CrossRef]
49. Brant, R. Assessing Proportionality in the Proportional Odds Model for Ordinal Logistic Regression. *Biometrics* **1990**, *46*, 1171–1178. [CrossRef] [PubMed]

50. Nauges, C.; Thomas, A. Privately operated water utilities, municipal price negotiation, and estimation of residential water demand; the case of France. *Land Econ.* **2000**, *76*, 68–85. [CrossRef]
51. Gilg, A.; Barr, S. Behavioural attitudes towards water saving? Evidence from a study of environmental actions. *Ecol. Econ.* **2006**, *57*, 400–414. [CrossRef]