The Effect of Water-Use Labeling and Information on Consumer Valuation for Water-Sustainable Food Choices in California

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ABSTRACT

The recent rise of "eco-labels" has created a market for sustainable food options. With recent droughts in California, an agricultural powerhouse, there is a need for increased water efficiency in food production. Currently there are no water-efficient food labels in the marketplace to guide consumers who want to decrease their water footprint and follow a more sustainable diet. I used discrete choice experiments, rooted in random utility theory (RUM) to document consumer valuation of water efficiency and the effect of information on preferences for attributes and products via discrete choice experiments. Survey respondents participated in four choice experiments for avocados, almonds, lettuce, and tomatoes. Choice data was analyzed using a conditional logit model. Findings show that consumers perceived high utility towards water-efficiency and had a high willingness to pay (WTP). An information treatment doubled consumer WTP for low-water showing that there is a knowledge barrier and potential for marketing water-efficient foods.

KEYWORDS

choice experiment, willingness to pay, water efficiency, food, California agriculture

INTRODUCTION

Water shortages due to four years of severe drought conditions in most of California has left many wondering about the future of food production of the state's $43 billion agricultural sector. California, a major producer of dairy, tree nut, and fruits and vegetables relies heavily on irrigation, much of which is supplied through various water projects (USDA 2015). Due to a lack of rain and a decreased snowpack in the Sierra Nevada mountains because of unseasonably warm weather, many reservoirs and lakes throughout the state were at record lows in 2015. It is estimated that there is a surface water deficit of 8.7 million acre-feet. Moreover, lack of surface water has lead to steadily declining groundwater reserves due to unsustainable water use in farming (Howitt et al 2015). While 2016 has seen substantial rain due to El Niño, increased reservoir levels, and snowpack, there are still concerns over long-term drought implications.

Climate change and the resulting drought are leading to a new, lower baseline to which the sector is already adapting. Under these water constraints, the system is showing signs of stress. In 2015 alone, the drought has caused crop revenue losses of up to $902 million, with losses of $250 million in the dairy industry and $100 million in the feedlot industry (Howitt et al 2015). There is also an increased fallowing of cropland due to lack of water, which is leading to rising food prices (Howitt et al 2015).

Changes such as shifting towards less water-intensive produce or breeding more water-efficient crops in areas experiencing exceptional drought can help relieve agricultural dependency on water resources.(FAO 2012). Virtual water of an item, defined as the amount of water used during the production process, from planting to processing to distribution of foods, can vary considerably from one crop to another. Some agricultural products are far more water-efficient than others. For example, animal products typically have a much larger water footprint overall (Mekonnen and Hoekstra 2012). Thus, it is not surprising that a diet high in animal products (mainly in Europe and the United States) uses 5 m^3, or about 1321 gallons, of water per capita per day, while diets low in animal products require about half (Renault 2002). There is also considerable variation between produce, with nuts and tree fruit being more water intensive than lettuce, for instance. Changing consumer dietary habits could have a significant impact on the sustainability of agriculture with regard to water constraints if they choose to purchase more water-efficient options.

Market-based mechanism and sustainable-production incentives can make California's agriculture sector to be more efficient in terms of water use. One market-based mechanism for addressing water constraints and mitigating the impact of agricultural production on the environment is "eco-labeling" of food products, which targets consumers who are willing to pay a premium for a sustainable product (Hallstein and Villas-Boas 2009). One study found that fewer than 20% of respondents believed they would know how to make the necessary changes to create a sustainable diet (Macdiarmid 2012). Eco-labels can be used to address this considerable barrier that many consumers face in choosing a sustainable diet. Consumers often lack the knowledge or ability to discriminate between what is sustainable and what is not (Smith 2008). Eco-labeling food has been shown to impact consumer choice. For example, since the creation of the USDA organic seal with the National Organic Program in 2000, organic food has been one of the fastest growing food sectors as a means to more sustainable consumption (Dimitri and Greene 2002; Seyfang 2007). With the aid of labeling, consumers are willing to pay more for what they perceive as the more environmentally friendly option (Kiesel and Villas-Boas 2007; Hallstein and Villas-Boas 2009). Providing consumers with water-use labeling may prompt them to lessen their dietary virtual water footprint. Changing food habits through information and labeling may have a significant impact on the water requirements of agriculture if consumer act to signals in the marketplace.

Consumers are often willing to consider paying a higher price for a sustainable choice, as indicated through labeling, but that information will not always alter their behavior (Hallstein and Villas-Boas 2009) which is influenced by other factors such as income and knowledge on environmental issues. Consumer awareness of the environment and the impact of their food choices is increasing, especially for high profile products such as beef. A higher willingness to pay (WTP) supports an increase in price for a specific attribute such as decreased virtual water footprint because of the additional benefit to the consumer (Abidoye et al. 2011). This implies that having previous knowledge of the effect of agriculture on water supply and other environmental concerns will increase consumer valuation for water-efficient products. Consumer valuation data will provide an important tool for policymakers regarding how to label and present food products (Lee and Hatcher 2001). One study found that water is among the most important attributes of an item, behind price, when evaluating average consumer preference. Large shifts in preferences means that it they are very sensitive to labeling (Tait et al 2011). Being able to distinguish food products in the market will enable consumers to act on their values when presented with a choice between a conventional and a sustainable good. Such changes in demand and consumer awareness could spark a major production shift, just as with organic agriculture did in recent years. Currently there is no data on consumer reaction to information on water-use in foods, which could be a powerful tool for farmers and policymakers in California in a future of water scarcity.

My central research question is: What is consumer valuation for water efficiency in food? To answer this, I pose the following sub-questions: How does water-use information affect purchasing decisions? What is the willingness to pay for water efficiency? Does additional information (treatment) affect WTP? Is there a preference of water-efficiency over organic? And then finally, how does demographic background affect consumer choice? I will answer these using a survey-based discrete choice experiment and logistic regression analysis to extract consumer utility and WTP.

EXTENDED INTRODUCTION

California agriculture and climate

California is the top agricultural state, leading the nation in production and total value of cash receipts, $46.4 billion in 2013. The dairy sector, which leads all other agricultural commodities in total receipts, was worth $7.62 billion in 2012 and produced almost 21% of the nation's milk, cheese, and other dairy products. The state produces a third of the nation's vegetables and two thirds of fruits and nuts. In fact, California is the sole producer—99% or more—of almonds, figs, grapes for raisins, olives, pistachios, dried plums, pomegranates, sweet rice, and walnuts, among other products in the United States. The state's top 20 agricultural commodities are worth more than $38 billion and twelve of them are worth more than $1 billion each (NASS 2013; Appendix A). Water scarcity will have a serious effect on the state's agricultural sector, when almond cultivation, for example, uses up to a gallon of water per nut and is one of the highest valued crops (Baldocchi 2015).

California agriculture relies heavily on irrigation, much of which is supplied through water projects and now, increasingly, groundwater reserves. However, 97% of California's $43 billion agricultural sector experienced anywhere from severe to exceptional drought in 2015 (USDA 2015). California's agricultural dominance is largely premised on the unusual abundance of surface water and groundwater readily available for agriculture. The extreme weather caused by climate change, suggests the possibility of more years of drought leading to a new normal of reduced water supply (Howitt et al. 2015). The Mediterranean climate that helps make California agriculture so productive also increases the strain on water resources because of short wet winters, and long, dry summers. Dennis Baldocchi (2015), suggests that to endure future years of water constraints, we must decide which crops to grow, how many acres of those crops do we need, and whether we are willing to pay for the true cost of the water to grow those crops. For example, water-intensive crops should be grown in states where water is more abundant and, thus, valued less. However, since agriculture is a part of our market-based economy, it is essential for some price-based mechanism to help shift supply and demand towards a more resilient agricultural sector.

Water footprint of agriculture

Virtual water varies greatly across California's top grossing agricultural commodities (Mekonnen and Hoekstra 2011, 2010; Table 1). This metric is important for evaluating water-intensity. The virtual water of a food product is the amount of water used per unit of food during its production (Renault 2002). This method of evaluating water-use in food choices has been used to compare the water footprint in different diets and foods. Almonds and other tree nuts, for example, require more water than fruits and vegetables. Even between produce there is large differences, such as the high water intensity of grapes versus tomatoes. Milk, eggs, beef, and other animal products also use much more water on a whole (Mekonnen and Hoekstra 2011). In response to the drought, there has been an increase in fallowing of irrigated acres and regional crop shifting, and groundwater depletion. Looking to the virtual water of crops being grown could be more meaningful.

Table 1: Value and Water Requirements[1] of California Top 20 Agricultural Commodities[2].

Commodity	Rank 2013	Value $1,000	Water Use m^3ton^{-1}	Water Use gal/lb
Milk and Cream	1	7,617,641	925.3	122.1396
Almonds (Shelled)	2	5,768,100	16,095	2,124.54
Grapes	3	5,585,584	2,400	316.8
Cattle and Calves	4	3,048,390	13,984	1,845.888
Berries, All Strawberries	5	2,200,729	374	49.368
Walnuts (Shelled)	6	1,795,800	9,280	1,224.96
Lettuce, All	7	1,679,164	237	31.284
Hay, All	8	1,569,780	907	119.724
Tomatoes	9	1,222,470	214	28.248
Nursery	10	1,219,800	NA	NA
Flowers and Foliage	11	1,130,523	NA	NA
Pistachio	12	1,034,000	11,363	1,499.916
Broccoli	13	844,920	285	37.62
Rice	14	789,728	1,673	220.836
Oranges, All	15	742,076	560	73.92
Cotton Lint, All	16	623,242	9,113	1,202.916
Carrots, Fresh	17	555,000	195	25.74
Celery	18	436,406	177	23.364
Peppers	19	434,261	7,611	1,004.652
Eggs, Chicken	20	380,038	2,962	390.984

[1] Water use reflects the global average water footprint for each corresponding crop and crop products (Mekonnen and Hoekstra 2011; Mekonnen and Hoekstra 2010).

[2] Ranking and value source: (NASS 2013).

Farmers across the state have made various adjustments to the drought in just the last four years, including increased fallowing, increased prices, layoffs, and regional crop shifting. In 2015 alone, more than 542,000 acres were left fallow in California, due to lack of water for irrigation. Farmers without access to surface water are forced to turn to groundwater stores to maintain normal production schedule, though expanded groundwater use is straining reserves and increasing costs for both farmers and future generations. The unsustainable depletion of groundwater stores—there is no regulation limiting the amount extracted on one's private land—makes California more vulnerable to future years of low water availability. The Sustainable Groundwater Management Act of 2014 attempts to mitigate groundwater depletion through a 27 year timeline for stabilization, but this timeframe is too long to address the unprecedented rate of depletion and ensure aquifer recharge (Howwitt et al 2015). Though groundwater can save perennial tree crops, such as almond orchards, and cut losses caused by drought, it is a temporary solution. Shifting production is another means of mitigating the impact of the drought: for example, in 2014, farmers in the Sacramento Valley increased processing tomato and decreased rice production acreage (Howwitt et al. 2015). Thoughtful shifts to less water-intensive crops will be an important long-term reaction to the probable new baseline of low water availability.

Water as an economic good

Diminishing the water footprint of California agriculture can be partially achieved by increasing demand for water-efficient produce grown in the state. However, consumers might lack the knowledge or ability to discriminate between the sustainability of products (Smith 2008). This gap may be bridged by eco-labels, which act as a signal in the marketplace (Hallestein and Villas-Boas 2007). Fewer than 20% of survey respondents believed they would know how to make the necessary changes to create a sustainable diet (Macdiarmid 2012). Yet consumer awareness is generally increasing, particularly for high profile products such as beef. A higher willingness to pay (WTP) indicates a potential increase in price for a specific attribute because of the additional utility the consumer receives (Abidoye et al. 2011). Consumer valuation results will provide an important tool for policymakers concerning how to label and present food products (Lee and Hatcher 2001). Consumers are either motivated by environmental concern or budgetary constraints (Hallestein and Villas-Boas 2007). Overall, estimations show that consumers are willing to pay more for products that are considered environmentally friendly (Kiesel and Villas-Boas 2007). Those who are unable to spend more on food with special attributes will not change their preferences with more information. Willingness to pay will often increase with income and education level, because wealthier and more educated consumers can generally afford, or are willing, to pay a premium on goods they perceive as more sustainable. Consumer WTP is also dependent on a respondents' level of awareness of environmental issues (Hallstein and Villas-Boas 2009). Having previous knowledge of the effect of agriculture on water supply and other environmental concerns will increase valuation for water-efficient products.

Assigning an economic value to water is difficult. Yet water is indeed a special, economic good for which there is not a substitute. Therefore pricing should not be left to the market, because doing so would conflict with water resource management and leave a irreplaceable resource vulnerable (Van der Zaag and Savenije 2006). The United Nation Food and Agriculture Association's (FAO) economic valuation of water resources in agriculture points out that water as a resource is scarce and limited, especially groundwater recharge. In addition, achieving water sustainability requires that there are no costs for future generations caused by present use. Ultimately some form of valuation will be essential for setting prices, extraction rate, and creating policy. Irrigation water value is much lower than domestic and industrial water use values (Turner et al 2004), which does not bode well for the future of agriculture in a low-water availability framework.

Conceptual framework

The theoretical framework of this study is based on Lancastrian consumer theory of utility maximization (Lancaster 1966). Lancaster (1966) suggests that a good itself does not give utility, rather the characteristics of the good give rise to utility. Consumer choices can be modeled using Lancastrian's random utility theory (RUM), which suggests that consumers derive utility from the attributes that make up a product (Lu et al. 2013; Tait et al. 2011). The individual possesses a utility function of different characteristics which he will try to maximize (Tait et al. 2011; Lancaster 1966). Individual *y* derives a certain utility from the attributes, $X_1+X_2+\ldots+X_n$ that make up product *i.* Total utility for individual *y* and alternative *i* is represented by the utility function:

$$U_{yi} = \beta_{0yi} + \sum\beta_n X_{yi} + \varepsilon_{yi}$$

where U_{yi} is a function of the sum of utilities, β_n is the marking utility of the *n*th attribute, *and* ε represents a degree of unobserved error in alternative *i* for person *y* (Lu et al. 2013; Tait et al. 2011; Gao and Schroeder 2009). Individual *y* will choose product *i* over product *j* if

$$U_{yi} = \beta_{0yi} + \sum\beta_n X_{yi} + \varepsilon_{yi} > \beta_{0yj} + \sum\beta_n X_{yj} + \varepsilon_{yj} = U_{yj}.$$

Following Lu et al. (2013), the probability of choosing product i over j can be rewritten as

$$P_{yi} = Prob(U_{yi} > U_{yj}).$$

Consumer *y*'s willingness to pay (WTP) for the *n*th attribute is the amount of money consumer *y* would be willing to pay, if *n* changes, in order to stay at their original utility level (Gao and Schroeder 2009), and can be represented as a ratio of marginal utilities:

$$WTP_n = \beta_n / \beta_{price}.$$

Methodology

Conjoint analysis versus discrete choice experiment

This study used a discrete choice experiment to evaluate consumer preferences for water as an attribute in food choices and calculated the difference in WTP between treatment and control groups to estimate the effect of information on relative preferences. Discrete choice experiments (DCE) and conjoint analysis (CA) are the two most common methods for gathering stated preference, and both are rooted in RUM (Lu et. al 2013). Both methods require a set of products made up of attributes. CA, which is rooted in marketing, economics, and physiology, asks respondents to rank the alternatives in order of preference. The relative of ranking of options yields a relative preference for each attribute as the respondent weighs attributes and makes tradeoffs (Carías Vega and Alpízar 2011). However, CA does not simulate a real marketplace scenario, in which a consumer has to pick only their top choice, like in choice experiments (Álvarez-Farizo and Hanley 2002). The key criticism of CA is that it does not address consumer behavior when faced with making a choice (Lu et. al 2013). DCE on the other hand, asks respondents to choose a single option, better simulating the context that consumers are normally presented with in the marketplace (Tait et al. 2011). There is also a "I would not purchase any of these" option to make the choice task more realistic (Gao and Schroeder 2009; Alfnes et. al 2006). Because DCE is a better model of food purchasing decisions, I used it in this study.

Stated preference

This study used stated preference over revealed preference. Stated preference has been widely used in the fields of agricultural, food, environmental, resource, and health economics since the 1990s. There are many ways to elicit a consumer's preferences without asking outright. Some economists argue that preferences revealed in the marketplace are more meaningful than stated preferences in a survey (Hallestien and Villas-Boas 2009). However, stated preference can be preferable to revealed preference when evaluating the value of goods and services not tangible in existing markets. Techniques include creating hypothetical markets and scenarios, causing survey respondents to ideally act as they would in a real marketplace (Carías Vega and Alpízar 2011). For the purpose of this study, stated preferences, through a discrete choice experiment, yielded the required results to understand consumer reaction to water-use and labeling on food choices.

METHODS

Survey development

Stated preference survey

This study used stated preference survey of discrete choice experiments. DCEs are based in Random Utility Theory (RUM), where an individual maximizes utility as a combination of part-worth utilities of different attributes of an object.

Survey implementation

I collected survey responses from 193 California residents via SurveyMonkey, using the platform's "audience," which is a database of respondents, and also a direct link to gather responses. SurveyMonkey ensures that there is no monetary prize to cause its audience to rush through to complete a survey. Rather, respondents decide which charity they want SurveyMonkey to donate for their responde. I added specification ensured that all responses were from California residents. This criterion was important to ensure that responses were from the area of interest, California, where drought is impacting California agriculture. There were 103 respondents in the control group and 90 in the treatment group. I entered survey data into the statistical program STATA, and then ran it through econometric models to extract information on consumer behavior and the effect of information.

Discrete choice experiment

I asked survey respondents to reveal their preferences for four food items: Haas avocado, almonds, head lettuce, and tomatoes (Table 2). These items were chosen because avocados and almonds are high-value tree crops that are less adaptable to yearly environmental factors. They require more water than many field crops because the trees need to be maintained and watered year-round. Tomatoes and lettuce represent less permanent, more adaptable crops with lower water footprints. Each food item has three attributes: water use, price, and if it is organically or conventionally grown. Water use has two levels, an average water use and an "efficient" water use. Since the attribute organic or conventionally grown is an attribute with only two levels, there are 2 x 2 = 4 possible attribute combinations per item. Price is determined by market data using the average price for conventional and organic versions of the food and adding a 20% price premium if the item has an "efficient" water footprint.

Table 2. Product attributes, levels, and combinations. For each item there are two levels of variety–conventional or organic–, two levels of water footprint–average and efficient–, and four price levels to portray the four combinations of variety and water footprint.

Item	Variety	Water footprint	Price ($/lb)
Hass Avocado			
	Conventional	Average (157 gal/lb)	$0.98
	Organic	Average (157 gal/lb)	$2.00
	Organic	Efficient (80 gal/lb)	$2.40
	Conventional	Efficient (80 gal/lb)	$1.18
Almond			
	Conventional	Average (1,715 gal/lb)	$5.99
	Organic	Average (1,715 gal/lb)	$11.59
	Organic	Efficient (1,450 gal/lb)	$13.90
	Conventional	Efficient (1,450 gal/lb)	$7.19
Lettuce (Head)			
	Conventional	Average (14.8 gal/lb)	$2.17
	Organic	Average (14.8 gal/lb)	$5.00
	Organic	Efficient (5.9 gal/lb)	$6.00
	Conventional	Efficient (5.9 gal/lb)	$2.60
Tomatoes (Fresh)			
	Conventional	Average (16.9 gal/lb)	$1.56
	Organic	Average (16.9 gal/lb)	$1.99
	Organic	Efficient (6.5 gal/lb)	$2.39
	Conventional	Efficient (6.5 gal/lb)	$1.87

Respondents are asked to indicate which item they would be most likely to buy, after taking into account their own preferences and budget. There was a fifth option for each individual, "I would not purchase any of these," to fully mimic a grocery shopping context because it is reasonable to assume that a consumer could opt out of purchasing altogether. Table 2 outlines the different product combinations. Each item was either conventional or organic, has an average or "efficient" water footprint, and four different price levels to reflect the attributes. The percentage of respondents choosing each combination of attributes of each item (Appendix B).

Role of information

For a random subset of the respondents, additional information on the California drought and its impact on agriculture came before the choice experiment. This information came in the form of a short summary statement and an infographic highlighting how much water goes into producing different foods. This was the survey treatment. The information concerning the drought and the variation between water intensity of foods acted as a primer for questions concerning preferences towards water efficient items. I then calculated the difference between treatment WTP and control WTP, as well as a treatment interaction logit model, to evaluate whether this subset of respondents reacted differently to water-usage of food and changed behavior accordingly. This method can be used only under the assumption that the control group is a good counterfactual to the treatment group. The control group performed the choice experiment without any additional information.

Demographics and psychographic makeup

Respondents were also asked demographic questions regarding income, age, gender, education, family size, and psychographic questions to evaluate how environmentally conscious they are. All respondents are California residents. The demographic makeup of survey respondents, and treatment and control groups, is compared to total California population (Table 3).

Table 3. Demographic summary statistics. Data from 2014 CA Census Fact Finder Database and demographic questions in survey. All units are percentage of respective population.

		Survey Sample			California
Variable	Category	Control (%)	Treatment (%)	Total (%)	Total population (%)
Gender					
	Male	47.57	46.67	47.15	49.70
	Female	52.43	53.33	52.85	50.30
Age					
	17 or younger	1.94	2.22	2.07	24.40
	18-20	3.88	2.22	3.11	5.60
	21-29	11.65	15.56	13.47	12.90
	30-39	14.56	10.00	12.44	13.80
	40-49	21.36	11.11	16.58	14.20
	50-59	16.50	27.78	21.76	12.80
	60 or older	30.10	31.11	30.57	16.30
Education					
	Less than high school degree	1.94	5.56	3.63	17.90
	High school degree or equivalent	4.85	4.44	4.66	20.90
	Some college but no degree	22.33	26.67	24.35	21.70
	Associate degree	5.83	2.22	4.15	7.80
	Bachelor degree	24.27	26.67	25.39	20.00
	Graduate degree	40.78	34.44	37.82	11.80
Household Income					
	Less than $25,000	14.56	14.44	14.51	20.40
	$25,000 to $49,999	11.65	14.44	12.95	21.10
	$50,000 to $74,999	11.65	18.89	15.03	16.70
	$75,000 to $99,999	19.42	12.22	16.06	12.20
	$100,000 to $124,999	7.77	15.56	11.40	7.40
	$125,000 to $149,999	9.71	8.89	9.33	7.50
	$150,000 or more	25.24	15.56	20.73	14.50
Race					
	White (Including Hispanic/Latino)	85.44	77.08	81.50	57.60
	Black or African-American	3.88	4.17	4.02	6.20
	American Indian or Alaskan Native	0.97	1.04	1.00	1.00
	Asian	2.91	7.29	4.97	13.00
	Native Hawaiian or Pacific Islander	0.97	1.04	1.00	0.40
	From Multiple Races	5.83	9.38	7.50	4.90
Total Count		103	90	193	38.8 million

The demographic makeup of the control and treatment groups was similar enough to assume that any differences would not affect the outcome of the experiment (Table 3). In the survey sample, ages "17 or younger" were underrepresented compared to the California population. Furthermore, the "50-59" and "60 or older" age group were overrepresented in the sample, suggesting that sample data is skewed towards older populations. Similarly, the sample demographic shows that education attainment levels of "Less than high school degree" and "High school degree or equivalent" were underrepresented in the sample and "Graduate degree" was overrepresented. All other education levels were accurately portrayed in the sample population. Income levels are fairly accurately represented, as was race and gender.

Another metric of interest was respondents' "Environmental Score" (Table 4). Respondents are presented with ten statements concerning climate change, green purchasing, and the drought and asked to indicate how much they agree with the preceding statement on a scale of 1 (strongly disagree) to 5 (strongly agree). A response of 1 indicates less environmental concern and suggests that they do not believe in immediate action or behavioral changes. A response of 5 indicates that the respondent is highly concerned with the environment. There is a neutral (3) option to rid of non-response bias.

Table 4. Environmental question summary statistics.

Question	Average (SE)
Climate change is a result of human activities and is already affecting people worldwide.	4.05 (0.089)
Protecting the environment should be given utmost priority, even if it causes slower economic growth and some loss of jobs.	3.81 (0.084)
It is the government's responsibility to impose high taxes on fossil fuels.	3.45 (0.097)
The U.S. government should impose stricter laws on pollution.	3.97 (0.087)
People should pay higher prices to address climate change.	3.19 (0.096)
There should be more investment using tax dollars in alternative fuels.	3.80 (0.092)
People should make lifestyle changes to reduce environmental damage.	4.20 (0.074)
It is important to purchase things that are more environmentally friendly, even at a greater cost.	3.74 (0.083)
The current generation has a responsibility to protect the environment for future generations, even if it leaves them less well off.	3.83 (0.085)
Personal food choices can affect the environmental impact of agriculture	3.96 (0.081)
Environmental Score	38.01 (0.720)

Based on the sum of their responses to the ten questions, respondents are given an "Environmental Score" that indicates their attitude towards climate change. The average response ranged from 3.19 to 4.2, with an average sum of 38.01, or 3.8 on average on each of the

10 questions (Table 4). I used this score to see if it affects consumer choices. A consumer with higher than the median environmental score is a "green" consumer.

Data and Summary Statistics

The choices respondents made, based on demographic background, environmental score, and treatment or control groups are shown below (Table 5).

Table 5. Summary statistics: demographic makeup on environmental score and choices.

	Environmental score		Share choice organic		Share choice efficient water footprint		Average price ($)	
Demographic Category	mean	SD	mean	SD	mean	SD	mean	SD
Total	38.01	10.00	0.27	0.45	0.63	0.48	2.96	3.14
White	37.66	10.27	0.27	0.45	0.66	0.47	3.07	3.12
Minority	39.26	8.90	0.27	0.45	0.52	0.50	2.57	3.21
Female	37.91	10.19	0.25	0.43	0.65	0.48	2.83	3.17
Male	36.08	10.80	0.24	0.43	0.56	0.50	2.80	2.98
High school or less	35.03	9.89	0.24	0.43	0.49	0.50	2.44	3.09
Bachelor or associate degree	38.21	9.33	0.22	0.42	0.64	0.48	2.93	2.90
Graduate degree	40.42	9.96	0.35	0.48	0.75	0.44	3.44	3.30
$49,999 or less	37.06	9.89	0.27	0.45	0.57	0.50	2.81	3.34
$50,000-$99,999	36.23	10.46	0.20	0.40	0.60	0.49	2.62	2.68
$100,000 or more	39.98	9.39	0.33	0.47	0.69	0.46	3.32	3.30
17 or younger	34.50	3.76	0.13	0.34	0.38	0.50	2.25	3.15
18-59	37.75	9.70	0.28	0.45	0.63	0.48	2.97	3.19
60 or older	38.83	10.85	0.26	0.44	0.66	0.47	3.00	3.03
Treatment	37.91	10.19	0.25	0.43	0.65	0.48	2.83	3.17
Control	38.10	9.85	0.30	0.46	0.61	0.49	3.08	3.12

Environmental scores ranged from 34.5 to 40.2, varying across groups. "Share choice organic" represents the fraction of events where a respondent choses an organic option. A mean of 0.27 for Total meant that survey respondents overall chose organic products 27% of the time. On the other hand, those with a graduate degree chose organic options 35% of the time. "Share choice efficient water footprint" is the fraction of events in which a respondent chose a water efficient product. For the total survey population, 63% of the time, a respondent chose a water efficient option. Similar to "share choice organic", the "Graduate degree" category of respondents chose the efficient water products with the highest frequency of all groups, 0.75. Average price is the average of all prices of items chosen, which is $2.96. If a respondent chose "I would not purchase any of these" the price is counted as "0."

The summary statistics of demographic makeup on environmental score and choice (Table 5) begins to describe variations in the data and interactions between groups. The treatment group has a lower organic choice mean than the control group, 0.25 versus 0.30, and a higher efficient water footprint choice, 0.65 versus 0.61. However, the treatment group has a lower average price, $2.83, than control group, $3.08. Conditional logistic regression will be able to better explain these variations.

Conditional logit model development

The first round of analysis of survey results used a simple logistic regression (logit,) without demographic variables. When demographic variables are added to the model,–age, household income, education, and race–the coefficient on the price, organic, and efficient water footprint parameters did not change significantly. This indicates that the sample of respondents is well-balanced in observable characteristics demographic, thus demographic variables can be left out of the model because hey are not influencing the results. However, in this simplest model the price coefficient was positive, which is counter-intuitive as a higher price normally corresponds to a smaller likelihood or purchase (i.e. I can expect that the coefficient would be negative). Once I added dummy variables of the four items is included in the model, becomes negative. This change occurs because when the type of item is not controlled for in the logit model, the differences in prices *between* the four items biases the price coefficient. Furthermore, while I did not find that observable characteristics of the individuals changed by results, one might suspect that unobservable characteristics could still be important. Thus I estimate a conditional logit model which includes a fixed effect dummy for each individual. Conditional logistic regression (clogit) allows me to control for how the both the observed and unobserved characteristics of an individual affect the probability of choosing some alternative. Finally, I introduce different interaction terms with treatment, environmental score, and demographic variables into this model to see if the results are heterogeneous by levels of these variables. In all regressions, the the outside option ("I would not purchase any of these") is normalized to zero, meaning choosing the outside option provides zero utility.

RESULTS

The results are presented in the following tables: coefficients on the conditional logit model (Table 6), willingness to pay for efficient water use and organic attributes between the control and treatment group (Table 7), and willingness to pay, or consumer value, per gallon of water saved by study average and item (Table 8).

Logistic regression results

The columns in Table 6 correspond to four different conditional logistic (clogit) regression models. Clogit I is a basic conditional logit model in which choice is the dependent variable and price, organic, and efficient water footprint are independent variables. The model is considered to be grouped by individual, which means that it includes fixed effects to control for the individual characteristics that affects their probabilistic behavior. *Price* is a categorical variable. Organic is binary and indicates if the item is organic or conventional. The *efficient water footprint* indicates if the item has an average or efficient water footprint. All three variables were statistically significant at $p<0.05$.

Clogit II is an added specification to Clogit I, in which I added treatment interactions to the model. This helps quantify if treated individuals are more willing to purchase the water efficient option, based on the water use and California drought informational treatment. The coefficient on *Price X Treatment* indicates the difference between the control group (*Price*) and the treatment group's (*Price X Treatment*) utility from price. This comparison was also the case for *Organic X Treatment* and *Efficient Water Footprint X Treatment* interactions. Only the *Efficient Water Footprint X Treatment interaction* is statistically significant at $p<0.01$.

Table 6. Conditional logit regression coefficients.

	Clogit I	Clogit II	Clogit III	Clogit IV
Price	-0.150**	-0.184**	-0.164*	-0.114
	(0.043)	(0.058)	(0.074)	(0.0834)
Organic	-0.485**	-0.256	-1.310***	-0.503
	(0.146)	(0.194)	(0.233)	(0.275)
Efficient Water Footprint	1.658***	1.417***	1.112***	1.246***
	(0.109)	(0.141)	(0.149)	(0.196)
Price X Treatment	—	0.0782	—	—
		(0.088)		
Organic X Treatment	—	-0.5329	—	—
		(0.297)		
Efficient Water Footprint X Treatment	—	0.588**	—	—
		(0.226)		
Price X Green	—	—	0.00025	—
			(0.094)	
Organic X Green	—	—	1.585***	—
			(0.311)	
Efficient Water Footprint X Green	—	—	1.274***	—
			(0.235)	
Price X College	—	—	—	-0.0514
				(0.0978)
Organic X College	—	—	—	0.0243
				(0.325)
Efficient Water Footprint X College	—	—	—	0.583*
				(0.236)
N	2880	2880	2880	2880
R2	0.1462	0.1513	0.1884	0.1534

Note: Coefficients listed, standard errors in parenthesis. Significance indicated by *p<0.05, **p<0.01, and ***p<0.001.

Clogit III examines the basic conditional logistic model with a "green" interaction. This metric is derived from the environmental score each respondent is assigned, based on their answers to environmental questions. Respondents in the top 50th percentile of environmental scores were indicated as being "green." A green consumer would hypothetically gain more utility from purchasing environmentally friendly options. The coefficient on *Organic X Green* and *Efficient Water Footprint X Green* were both positive and significant suggesting that a green consumer gains more utility from water efficiency and organic options than a non-green consumer. A green consumer gains positive utility while a non-green consumer perceives negative utility from organic. Utility from water-efficiency for both green and non-green consumers are both positive, with green consumers gaining more.

The fourth column, Clogit IV (Table 6) describes the clogit model with a college education interaction. The "College" variable includes respondents who completed a college degree, associates degree, or graduate degree. I hypothesize that a more educated individual will value environmental options higher and therefore may be more willing to pay for such options. The *Efficient Water Footprint X College* coefficient is positive and significant at $p<0.05$. The other interactions, *Organic X College* and *Price X College*, were not statistically significant at this level.

Willingness to pay

Based on the coefficients on the conditional logit model with treatment interactions (Table 6, Column 2), I can estimate the willingness to pay in dollars for the organic and water-efficient labels. WTP for *Water Efficient Footprint* and *Organic* attributes (Table 7). WTP is calculated by dividing the coefficient on the attribute of interest by the *price* coefficient. I then compared between control and treatment groups below (Table 7, Column 3) by taking the difference. The last column calculates the difference between the control and treatment group, or the effect the treatment had on individual valuation of the attributes.

Table 7. Willingness to pay for water efficiency and organic, by treatment.

	Control	Treatment	Difference
	WTP ($)	WTP ($)	WTP ($)
Water Efficient Footprint	7.710	18.987	11.277
Organic	-1.394	-7.475	-6.081

Table 8 describes WTP for the water efficient option in greater detail. First, the WTP for Water Efficient Footprint in Table 7 is just a valuation indicator of that label. More specifically, it is the amount of money that a consumer was willing to spend to purchase a water efficient item over an average water use item, regardless of water savings. It represents the WTP for average water savings. Table 8 calculates the marginal WTP for each gallon saved based on each item and the average water savings. For example, a consumer was willing to spend \$7.71 on average to purchase the low water almond option. If this saved 265 gallons, then their WTP was \$7.71/265 gallons water saved = \$0.029/gallon water saved. An individual in the treatment group, however, was willing to spend \$18.987 for the low water option, or \$0.072/gallon water saved. The difference between the treatment and control individual in this example was an increase of \$0.043/gallon of water saved for the treatment group.

Table 8. Willingness to pay for water savings by gallon.

	Control	Treatment	Difference
Item	WTP (\$/gal)	WTP (\$/gal)	WTP (\$/gal)
Avocado	0.100	0.247	0.146
Almond	0.029	0.072	0.043
Lettuce	0.866	2.133	1.267
Tomato	0.741	1.826	1.084
Average	0.085	0.210	0.125

DISCUSSION

I found that consumers gained significant positive utility from purchasing a low-water option and maintained a higher willingness to pay for water efficiency than for organic. There was a significant difference between the treatment and control groups, suggesting that additional information on the drought and agriculture did affect consumer purchasing behaviors. The overall impact of the treatment was to double WTP. These results help address the gap in knowledge on consumer valuation and response to water-use data in food production and valuation of savings. Results also suggest that there is a gap in consumer knowledge of drought, agriculture, and food choices.

Results of the conditional logistic regression show that, on average, consumers gained significant positive utility from *water-efficiency* and negative utility from *price* increases and *organic* production, suggesting that water-efficiency is an important attribute of an item and significantly influences consumer valuation and preferences. The negative utility from the *organic* attribute is inconsistent with findings in other research where the *organic* attribute was the attribute of interest (Kiesel and Villas-Boas 2007) that find a higher valuation for an organic product. Valuation of water-efficiency increased with treatment, college education, and a high green score. Other demographic variables such as age, income, race, did not have statistically significant impact on consumer utility. The treatment interaction clogit suggests that without treatment consumers gained a marginal utility of 1.12 while treated individuals gained an additional 0.588 of utility. Treated individuals lost even more utility from the *organic* attribute, -0.5329, compared to the control group. They similarly gained a small amount of utility from *price*, meaning they are slightly less price averse than the treatment group. These results suggest that, with the drought and agriculture informational treatment, consumers chose to purchase the low-water option over the organic option, but not both because of the price premium. Green consumers were also less price averse than non-green consumers. Contrary to the treatment group, green consumers gained significant positive utility from both organic and low-water attributes. This result means that green consumers are more likely to purchase items that are both organic and low-water, compared to consumers with low environmental inclinations. College educated survey respondents gained utility from *water efficiency* as compared to non-educated respondents, with little to no significant change in utility based on *price* or *organic*, suggesting that upon seeing water labeling they were more likely to understand the consequences of their purchasing decisions. These findings are consistent with Kiesel and Villas-Boas (2007) who found that education levels and environmental awareness may have influenced their results. This is contrary to Heiman and Zilberman (2011) who found that an individual with knowledge of an issue is less affected by framing framing, whereas green and more educated consumers had higher valuation with the water labeling.

WTP results show that consumers were willing to pay a premium for water efficiency which doubled under the informational treatment. The coefficients on *price* and *water efficiency* parameters in the treatment interaction regression (Clogit II, Table 6) determined WTP for the low-water alternative. Untreated respondents were willing to pay a $7.71 premium for water-efficiency on average for all four items. The treatment group was willing to pay a premium of $18.99, more than double the control group. Comparatively, the control group was only WTP -

$1.39, or “willing to accept”, for the organic option. The control group would essentially need to be paid $1.39 to accept an organic item and remain at their original utility level. The treatment group decreased in WTP by more than $6 to -$7.48. These differences in WTP suggest that the control group values water efficiency more than organic production–perhaps because of the prominence of the drought in the news, which only increased with treatment. Consumers made tradeoffs between these two attributes giving preference to water efficiency. This is consistent with other findings that consumers are willing to pay a premium for environmentally friendly options. A premium for water-efficiency could help California become less reliant on water for agriculture and alleviate drought tension while inducing farmers to adopt water-saving techniques and products.

Survey responses suggest that overall, the average consumer is willing to pay $0.085 per gallon of water saved in production process, and $0.21 per gallon with treatment. Valuation per gallon ranged from $0.029 to $2.13. This suggests that marketing water efficiency, with a price premium could directly affect the water use of agriculture.

Consumer WTP was higher for water efficiency after being prompted with information because of increased utility and decreased price aversion. Treated individuals were more likely to choose *water-efficient* products over *organic*. Treatment also had a significant effect on utility from *water-efficiency*. With information, the treatment group valued organic produce less, suggesting a tradeoff between water efficiency and organic produce. These results suggest that there is a gap of consumer knowledge between the amount of water used for agriculture, and their subsequent food choices, and the grocery store.

Limitations and Future Directions

This study faced several limitations. Time constraints did not allow for random sampling to administer the survey in person, thus stated preferences were needed. The sample size was small because of budget constraints. Furthermore, sample design was a limitation: other choice experiments in the literature create many sets of attributes and more levels of attributes to extract

WTP of a key attribute (Lu et al, Alfnes et al, Gao et al). This survey design was a preliminary method to extract valuation of water efficiency.

Future studies should create a more complex attribute set, with more levels and attributes to fully extract WTP for water savings. Future research can also look into the most effective labeling to convey water savings/efficiency to the consumer, and study labeling between products using a comparison in grocery stores. Another potential for research is identifying low-water items versus high-water items, such as comparisons between different proteins or fruits and vegetables. This could enable consumers to choose low water menus and diets. This would be after maximizing water efficiency within each food production cycle.

Broader Implications/Conclusions

Respondents overwhelmingly valued water-efficiency, which strengthened with treatment. This suggests that there is a crucial knowledge gap that policymakers should address. Results indicate that more research is needed into consumer valuation for water efficiency as a powerful political tool to curb the use of water in agriculture. Labeling, thus signaling a consumer to pay a premium, could create incentives for farmers to invest in water efficiency, thus decrease the water footprint of California as a whole. This would be a significant step towards strengthening California's agricultural resiliency in the face of continued climate change and a low-water future.

ACKNOWLEDGEMENTS

Thank you Kurt Spreyer and Tina Mendez for your guidance throughout this process and leading our ESPM 175 class. Thank you Kurt for reading every draft of every section I wrote. Thank you Sofia Villas-Boas and Becca Taylor for your help and mentorship, and for being amazing role models in academia. Finally, thank you Jordan Cheng and Akmaral Zhakypova for being a great Economixxx group and moral support, my roommate and friends who had to listen to me talk about this for three semesters, and my family for everything else.

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APPENDIX

Appendix A: 2013 Value and Water Requirements[3] of California's Top 20 Agricultural Commodities[4], with emphasis on the more water-intensive commodities.

Commodity	Rank (2013)	Value ($1,000)	Total water Use (m^3ton^{-1})	Water Use (gal/lb)
Almonds (Shelled)	2	5,768,100	16,095	2,124.54
Cattle and Calves	4	3,048,390	13,984	1,845.888
Walnuts (Shelled)	6	1,795,800	9,280	1,224.96
Pistachio	12	1,034,000	11,363	1,499.916
Rice	14	789,728	1,673	220.836
Cotton Lint, All	16	623,242	9,113	1,202.916
Peppers	19	434,261	7,611	1,004.652
Eggs, Chicken	20	380,038	2,962	390.984

[3] Water use reflects the global average water footprint for each corresponding crop and crop products (Mekonnen and Hoekstra 2011; Mekonnen and Hoekstra 2010).

[4] Ranking and value source: (NASS 2013).

Appendix B: Choice experiment results (% of choices)

Item	Description	Control (%)	Treatment (%)	Total Survey (%)
Hass Avocado				
	$0.98/lb, Conventional, Average Water Footprint (157 gal/lb)	8.74	10.00	9.33
	$2.00/lb, Organic, Average Water Footprint (157 gal/lb)	6.80	1.11	4.15
	$2.40/lb, Organic, Efficient Water Footprint (80 gal/lb)	22.33	21.11	21.76
	$1.18/lb, Conventional, Efficient Water Footprint (80 gal/lb)	46.60	46.67	46.63
	I would not purchase any of these.	15.53	21.11	18.13
Almonds				
	$5.99/lb, Conventional, Average Water Footprint (1,715 gal/lb)	19.42	11.11	15.54
	$11.59/lb, Organic, Average Water Footprint (1,715 gal/lb)	7.77	3.33	5.70
	$13.90/lb, Organic, Efficient Water Footprint (1,450 gal/lb)	11.65	15.56	13.47
	$7.19/lb, Conventional, Efficient Water Footprint (1,450 gal/lb)	33.98	32.22	33.16
	I would not purchase any of these.	27.18	37.78	32.12
Lettuce (Head)				
	$2.17/lb, Conventional, Average Water Footprint (14.8 gal/lb)	15.53	10.00	12.95
	$5.00/lb, Organic, Average Water Footprint (14.8 gal/lb)	6.80	3.33	5.18
	$6.00/lb, Organic, Efficient Water Footprint (5.9 gal/lb)	22.33	16.67	19.69
	$2.60/lb, Conventional, Efficient Water Footprint (5.9 gal/lb)	41.75	55.56	48.19
	I would not purchase any of these.	13.59	14.44	13.99
Tomatoes (Fresh)				
	$1.56/lb, Conventional, Average Water Footprint (16.9 gal/lb)	9.71	12.22	10.88
	$1.99/lb, Organic, Average Water Footprint (16.9 gal/lb)	10.68	1.11	6.22
	$2.39/lb, Organic, Efficient Water Footprint (6.5 gal/lb)	31.07	36.67	33.68
	$1.87/lb, Conventional, Efficient Water Footprint (6.5 gal/lb)	35.92	36.67	36.27
	I would not purchase any of these.	12.62	13.33	12.95