Volume Title: Agricultural Productivity and Producer Behavior

Volume Authors/Editors: Wolfram Schlenker, editor

Volume Publisher: University of Chicago Press

Volume ISBNs: 978-0-226-61980-4 (cloth); 978-0-226-61994-1 (electronic)

Volume URL: https://www.nber.org/books-and-chapters/agricultural-productivity-and-producer-behavior

Conference Date: May 11-12, 2017

Publication Date: November 2019

Chapter Title: Willingness to Pay for Low Water Footprint Foods during Drought

Chapter Author(s): Hannah Krovetz, Rebecca Taylor, Sofia B. Villas-Boas

Chapter URL: https://www.nber.org/books-and-chapters/agricultural-productivity-and-producer-behavior/willingness-pay-low-water-footprint-foods-during-drought

Chapter pages in book: (p. 251 – 291)

8

Willingness to Pay for Low Water Footprint Foods during Drought

Hannah Krovetz, Rebecca Taylor,
and Sofia B. Villas-Boas

8.1 Introduction

In January 2014, the governor of California declared a Drought State of Emergency, asking all Californians to reduce water consumption by 20 percent.[1] While droughts are a recurring feature of California's climate, the drought beginning in late 2011 was the driest and warmest drought on record, putting California agriculture under stress (Hanak et al. 2015).[2] California—a major producer of dairy, tree nuts, fruits, and vegetables—relies heavily on irrigation, much of which is supplied by the state's extensive system of water supply infrastructure—reservoirs, managed groundwater basins, and interregional conveyance facilities.[3] Farmers have taken measures to adapt to drought conditions, such as by shifting toward less

Hannah Krovetz is an analyst at Analysis Group.
Rebecca Taylor is an assistant professor in the School of Economics at the University of Sydney.
Sofia B. Villas-Boas is a professor of agricultural and resource economics at the University of California, Berkeley.

We thank Peter Berck and participants at the NBER Understanding Productivity Growth in Agriculture Conference and especially Dmitri Taubinsky, Wolfram Schlenker, Christine Carroll, and Marca Weinberg for their discussion and suggestions. We thank the Giannini Foundation and the College of Natural Resources' Sponsored Program for Undergraduate Research for financial support in the survey implementation. For acknowledgments, sources of research support, and disclosure of the authors' material financial relationships, if any, please see https://www.nber.org/chapters/c13949.ack.

1. Source: California Department of Water Resources, "Governor's Drought Declaration," accessed April 28, 2017, http://www.water.ca.gov/waterconditions/declaration.cfm.

2. In 2015, the drought 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 was also an increased fallowing of cropland due to lack of water, which led to rising food prices (Howitt et al. 2015).

3. California Department of Water Resources, "Drought in California," accessed April 28, 2017, http://www.water.ca.gov/wateruseefficiency/docs/2014/021114_Kent_Drought2012.pdf.

water-intensive crop varietals and by adopting more water-efficient irrigation methods (Hanak et al. 2015).[4] Given that the region may increasingly experience high temperatures and low precipitation flows (Mann and Gleick 2015), is there a market for consumers to compensate farmers for adopting more water-efficient production practices?

The rise of eco-labels has created a market for sustainable food options; however, currently a "low water footprint" label is not available to guide consumers who want to decrease the water footprint of their food consumption. Virtual water of an item—defined as the amount of water used during the entire production process, from planting to processing to distribution—varies greatly across California's top-grossing agricultural commodities (Mekonnen and Hoekstra 2011).[5] Changing consumers' dietary habits may have a significant impact on the sustainability of agriculture with regard to water constraints if consumers choose to purchase more water-efficient options. This chapter empirically assesses whether consumers respond to information on the water footprint of the food they choose and tests whether providing additional information on drought severity sways consumers to choose low water footprint (LWF) food options.

We investigate whether consumers are willing to pay for LWF agricultural products by designing and implementing a choice experiment via an online distributed survey of California consumers.[6] Before the choice experiment, we collect data on respondents' demographic characteristics and stated environmental concern. For the choice experiment, we present the respondents with four food products: avocados, almonds, lettuce, and tomatoes. Within each food product, survey respondents are asked their purchase choice among options that vary by production method (conventional or organic), water footprint (average or LWF), and price. In addition, we implement an information treatment in the survey design. Half of the respondents are randomly assigned to a treatment group, where they are briefed before the choice experiment about the drought severity in California. The control group is instead taken directly to the choice experiment, without additional information on the drought.

Using the survey data, we estimate a discrete choice model for consumer preferences, where a choice is defined as a bundle of attributes: product type, price, an organic indicator, and an LWF indicator. From the structural demand model parameters, we obtain estimates of the willingness to

4. Climate change and the resulting drought are leading to a new, lower baseline to which the agricultural sector is already adapting.

5. While nuts and tree fruit are more water intensive than lettuce, animal products such as milk, eggs, and beef are more water intensive than plant crops (Mekonnen and Hoekstra 2011). Thus it is not surprising that a diet high in animal products (mainly in Europe and the United States) uses about 1,321 gallons of water per capita per day, while diets low in animal products require about half that amount (Renault 2002).

6. Given that water usage labels currently are not implemented in the retail setting, we cannot use scanner data to measure actual consumer responses.

pay (WTP) for the various specified product attributes. In addition, we test whether revealing information on the drought matters for the WTP estimates. We are able to present novel findings in terms of heterogeneity of WTP along the respondents' demographics and their environmental scores and the role of drought information on WTP. Finally, by simulating a variety of changes in the choice set facing consumers, we obtain estimates of counterfactual choices under alternative policy scenarios and calculate the resulting welfare changes, measured as changes in the distribution of consumer surplus. We also relate the individual-level changes in consumer surplus to the demographic characteristics of the respondents.

We find that, on average, consumers have a significant positive marginal utility toward water efficiency and estimate that there is an implied positive willingness to pay for water efficiency of about 11 dollars. This positive WTP means that respondents are on average willing to pay 12 cents for each gallon of water saved. Moreover, informing consumers about the drought severity increases consumers' WTP for the LWF options, albeit not significantly. We additionally explore heterogeneity in WTP based on crop type and consumer characteristics. We find differences in the WTP along respondents' stated environmental concern, which is measured by level of agreement with statements pertaining the environmental issues and policies. There is also significant heterogeneity with respect to education and race. Using counterfactual simulations of removing LWF labels and drought information from the choice set attributes, we estimate changes in choices that imply significant consumer surplus losses, especially for the subgroup of respondents who are white, have attained higher levels of education, and have higher environmental scores.

The contribution of our chapter is twofold: (1) to estimate stated preferences and corresponding WTP for water efficiency in the production of crops and (2) to investigate whether consumers respond to information about drought severity and the water footprints of products in their choice sets. The availability of information about a product's attribute, such as water footprint, does not necessarily mean consumers will incorporate it into their decisions and alter their behavior. Our study provides a distribution of WTP estimates for LWF food options during drought years and an empirical test of whether consumers directly incorporate available information. In so doing, we equip resource managers with important information on the efficacy of LWF labels as well as a barometer reading on consumer stated preferences.

The rest of the chapter proceeds as follows. Section 8.2 reviews the related literature. Section 8.3 describes the empirical setting and the research design (i.e., the choice experiment and identification strategies) and summarizes the data. Section 8.4 outlines the model to estimate consumer choices and willingness to pay for product attributes. Section 8.5 presents the results of the choice model and discusses the findings in terms of the average WTP and the distribution of WTP in the sample. Section 8.6 derives the method to perform simulations and discusses the choice and welfare changes due to a counterfactual policy scenario. Finally, section 8.7 concludes and presents avenues of future research.

8.2 Literature Review

Related literature investigates consumer knowledge and market mechanisms to nudge consumers toward sustainable food products. With respect to consumer knowledge, Macdiarmid (2012) finds that fewer than 20 percent of respondents believe they would know how to make the necessary changes to create a sustainable diet. Smith (2008) also discusses how consumers often lack the knowledge or ability to discriminate between what is sustainable and what is not. However, Tait et al. (2011) find that, when evaluating consumer attitudes toward sustainability attributes, water efficiency is among the most important attributes of a food item, behind price and carbon footprint. With respect to market mechanisms, numerous studies have shown that providing consumers with information about product sustainability through "eco-labels" impacts consumer choices, such as the USDA organic seal (Kiesel and Villas-Boas 2007), sustainable seafood advisories (Hallstein and Villas-Boas 2013), dolphin-free tuna labels (Teisl, Roe, and Hicks 2002), and environmentally certified wood products (Aguilar and Vlosky 2007). Therefore, given consumers' stated lack of knowledge on the sustainability of their diets and the effectiveness of eco-labels in other settings, this chapter contributes to the literature by estimating how much consumers would value a water footprint label.

We follow closely and expand the existing revealed and stated preference literature, which uses a variety of reduced form and structural approaches to infer the value consumers place on product attributes that are not observable or tasteable by consumers at the point of purchase (such as organic, vitamin-fortified, dolphin-safe, free-range, rBGH-free). In the reduced-form context, hedonic price model approaches have been used to estimate relative values for food product attributes (Asche and Guillen 2012; Roheim, Gardiner, and Asche 2007; Roheim, Asche, and Santos 2011; Jaffry et al. 2004; McConnell and Strand 2000). Structurally, demand-system approaches are estimated to place a willingness to pay for product attributes (Alfnes et al. 2006; Teisl, Roe, and Hicks 2002). Our work is more closely related to this second literature stream and is the first to use these methods to place a value on water efficiency in the production of food and to ask whether consumers might be willing to pay for reduced environmental disamenities associated with food production.

While there are several means of agricultural adaptation in the context of water constraints and droughts—such as the observed increase in fallowing of irrigated acres, regional crop shifting, and groundwater depletion

(Howitt et al. 2015)—this chapter investigates whether there is willingness to pay for fewer gallons of water used within crop types. Changing food habits through information and labeling may have a significant impact on the water requirements of agriculture if consumers react to signals in the marketplace. A higher 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). There is very little, if any, empirical evidence on consumer reactions to information on water use in food production, and this chapter fills this gap in the literature. 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 organic agriculture did in the 2000s (Dimitri and Greene 2002).

8.3 Empirical Setting, Survey Design, and Data

We designed and implemented a choice experiment, with an information treatment, via an online survey of California consumers.[7] We collected survey responses from 193 California residents. For each of the respondents, we first asked for information on their demographic characteristics (i.e., gender, age, education, and race). Second, we asked respondents to answer whether they agreed or disagreed with 10 environmentally related statements in order to construct a measure of each respondent's environmental score. Finally, we collected data on the respondents' choices among options to purchase four food products: avocados, almonds, lettuce, and tomatoes. These four crops are highly ranked in terms of California's agricultural value and represent approximately 5 percent of California's 25.5 million operated farm acres.[8] In 2015, California produced more than a third of the country's vegetables and two-thirds of the country's fruits and nuts.[9] Moreover, in 2015, almonds were California's second most valued commodity ($5.33 billion), lettuce was fifth ($2.25 billion), and tomatoes were seventh (1.71 billion).[10]

In addition, we implemented an information treatment in the survey

7. The survey company ensured that there is no monetary prize to cause its audience to rush through to complete a survey. Rather, respondents decide which charity they want the survey company to donate for their response.

8. Source: National Agricultural Statistics Service, United States Department of Agriculture, "2015 State Agriculture Overview," accessed December 21, 2016, https://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=CALIFORNIA.

9. Source: California Department of Food and Agriculture, "California Agricultural Production Statistics—2015 Crop Year Report," accessed April 28, 2017, https://www.cdfa.ca.gov/statistics/.

10. Source: California Department of Food and Agriculture, "California Agricultural Production Statistics—2015 Crop Year Report," accessed April 28, 2017, https://www.cdfa.ca.gov/statistics/.

design. Half of respondents were randomly assigned to a treatment group, where they were briefed about the drought severity in California before the choice experiment. The remaining half in the control group got taken directly to the choice experiment, without information on the drought.

To base the choice experiment on realistic numbers, we collect industry estimates on the virtual water used in avocado, almonds, lettuce, and tomatoes. Recall that virtual water is defined as the amount of water used per unit of food during its production (Renault 2002). The average water footprint displayed to survey respondents in our study—in terms of gallons per pound of product produced—is 157 gallons per pound for avocados, 1,715 gallons per pound of almonds, 14.8 gallons per pound for lettuce, and 16.9 gallons per pound of tomatoes.

The experiment asked respondents to choose, for each of a set of horticultural crops, between organic and conventional methods, with average water footprint and low water footprint. This 2 × 2 matrix gives rise to variation, which allows us to distinguish between organic methods and water efficiency—a specific environmental amenity. What we do not allow is for respondents to switch between different horticultural crops directly, while indirectly they may stop buying a crop and start buying a new one after receiving information on water usage.

8.3.1 Experimental Choice Design

This study uses a discrete choice experiment (1) to evaluate consumer preferences for water footprint as an attribute of food choices and (2) to calculate the difference in WTP between a treatment group with additional drought information and a control group.[11] Discrete choice experiments are among the most common methods for gathering stated preference and are rooted in Random Utility Models. The first step is to define a product as being made up of a set of attributes. Then respondents are asked to choose a single option, simulating the context that consumers are normally presented with in the marketplace (Tait et al. 2011). There is also an "I would not purchase any of these" option to allow for identification and counterfactual simulations (Gao and Schroeder 2009; Alfnes et al. 2006).[12]

We asked survey respondents to reveal their preferences for five different options within each of four food items—Haas avocados, almonds, head lettuce, and tomatoes—as can be seen in table 8.1. These items were chosen

11. See figure 8A.1 for the survey instrument. The information concerning the drought acts as the treatment, preceding the questions concerning preferences toward water footprint and organic production in food choices (i.e., the treatment information about the drought preceded the avocado first-choice question for the treatment group in figure 8A.1). The control group performed the choice experiment in figure 8A.1 without any additional information.

12. If we do not include an outside option, simulations that increase attributes in a way that the relative ratio of such attributes remains unchanged (such as all prices doubling) will imply that the relative probabilities of choosing the options also remains unchanged, and this is not reasonable if, for example, consumers are budget constrained.

Table 8.1 **Choice set design: Production method, water footprint, and price**

Product	Production method	Water footprint (gal/lb)	Price ($/lb)
Hass avocado			
	Conventional	Average (157)	0.98
	Organic	Average (157)	2.00
	Organic	Efficient (80)	2.40
	Conventional	Efficient (80)	1.18
Almond			
	Conventional	Average (1,715)	5.99
	Organic	Average (1,715)	11.59
	Organic	Efficient (1,450)	13.90
	Conventional	Efficient (1,450)	7.19
Lettuce (head)			
	Conventional	Average (14.8)	2.17
	Organic	Average (14.8)	5.00
	Organic	Efficient (5.9)	6.00
	Conventional	Efficient (5.9)	2.60
Tomatoes (fresh)			
	Conventional	Average (16.9)	1.56
	Organic	Average (16.9)	1.99
	Organic	Efficient (6.5)	2.39
	Conventional	Efficient (6.5)	1.87

Note: 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 production method and water footprint. For all products, an option "I would not purchase any of these" was also given to respondents.

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 footprint, price, and production method (either conventional or organic). Water footprint has two levels, average and low (or "efficient"). Since the production method and water footprint attributes both have two levels, there are $2 \times 2 = 4$ possible attribute-combinations per item, not counting price. Finally, we use the average price for conventional and organic versions of the products. In the choice options presented in the experiment, we add an invented 20 percent price premium if the item has efficient water use.

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 was given to respondents in the form of a short summary statement and an infographic highlighting how much water goes into producing different foods. The information concerning the drought acts as a primer, or treatment, preceding the choice experiment questions. The control group performed the choice experiment without any additional

Table 8.2 **Summary statistics**

		California population*	Treated group respondents	Control group respondents	Total respondents
		Panel A. Demographics			
Gender	Male	49.7	53.06	52.29	52.66
	Female	50.3	46.94	47.71	47.34
Age	17 or younger	24.4	1.83	2.04	1.93
	18–59	59.3	66.06	66.33	66.18
	60 or older	16.3	32.11	31.63	31.88
Education	Less than some college	60.4	27.78	37.76	32.52
	Associate degree, bachelor degree	27.8	31.48	29.59	30.58
	Graduate degree or more	11.8	40.74	32.65	36.89
HH income	$49,000 or less	41.5	26.42	31.25	28.71
	$50,000–$99,999	28.9	30.19	29.17	29.70
	$100,000 or more	29.4	43.40	39.58	41.58
Race	White (including Hispanic)	57.6	83.64	76.53	80.29
	Black, Asian, and other minorities	42.4	16.36	23.47	19.71
Number of observations		38.8 million	110	98	208
	Panel B. Summary statistics of survey responses				
	Organic (share)		25.26	30.45	28.00
	LWF (share)		65.56	62.50	63.94
	None of the options (share)		20.92	17.05	18.87
	Average price of chosen options		2.86	3.14	3.01

Source for the California Data: 2014 CA Census Fact Finder Database.

information. By comparing average responses in the treatment and control groups, we can test the role of information on food choices and on the estimates of WTP inferred via the structural choice model. This is done under the assumption that the control group is a good counterfactual to the treatment group. The next subsection analyzes the balance of treatment and control groups and presents the summary statistics of the data used in the analysis.

8.3.2 Survey Data Summary Statistics

The survey instrument was sent to a total of 208 respondents, where the sample size was determined by financial constraints. Summary statistics of our data set are presented in table 8.2. This table is organized in two panels. In panel A, the demographic makeup of survey respondents in the treatment and control groups is compared to the total California population. In panel

B, we present the share of respondents choosing the organic and low water footprint attributes in the treatment and control groups.

In panel A of table 8.2, ages "17 or younger" in the survey sample are underrepresented compared to the California population. Furthermore, the "50–59" and "60 or older" age groups were overrepresented in the survey sample, suggesting that the sample data are skewed toward older populations. Similarly, panel A shows that education attainment levels of "Less than high school degree" and "High school degree or equivalent" are underrepresented in the survey sample and "Graduate degree" is overrepresented. Income levels in the sample overall are fairly representative of the California population, as is race and gender. When comparing the treatment and control groups to each other, we have balance across the demographic variables, with the makeup of the control and treatment groups similar for all rows in panel A.[13]

Turning now to the bottom panel B of table 8.2, we present survey response summary statistics for the share of respondents choosing organic and low water footprint (LWF) options and the average price of the alternative chosen. The row titled "Organic (share)" represents the fraction of events where a respondent chooses an organic option. A mean of 28 for the total means that survey respondents overall chose organic products 28 percent of the time. "LWF (share)" is the fraction of events in which a respondent chooses the lower water footprint option. For the total survey population, respondents choose a water-efficient option 64 percent of the time. Average price is the average of all prices of items chosen, which is \$3.01. If a respondent chooses "I would not purchase any of these," the price is defined as zero. The treatment group has a lower average organic choice share than the control group (25 percent versus 30 percent) and a higher average LWF choice share (66 percent versus 63 percent). The treatment group has a lower average price paid for the chosen alternatives than the control group (\$2.86 versus \$3.14), which aligns with the treatment group choosing the \$0 outside option more often (21 percent versus 17 percent).

Next we use the survey data to construct a measure of environmental concern of each respondent based on the degree of agreement/disagreement with a series of 10 statements regarding environmental issues and policies. Table 8.3 lists each of 10 statements and reports average survey responses. For each statement, we assign a value of 5 if the response is "Strongly agree" and 1 if the response is "Strongly disagree." The measure of environmental concern of each respondent, henceforth called environmental score, is the

13. An illustration of the balance of demographics in the control and treated group is presented in figures 8A.2 and 8A.3. We cannot reject that the average is similar between control and treated groups for any of the demographic variables. Moreover, we cannot reject the null in a Kolmogorov Smirnov test for equality of distributions between treatment and control groups for education (p-value = 0.936) and income (p-value = 0.481).

Table 8.3 **Response summary statistics for ten statements underlying environmental score**

Statement	Average (standard error)
1. Climate change is a result of human activities and is already affecting people worldwide.	4.05 (0.089)
2. Protecting the environment should be given utmost priority, even if it causes slower economic growth and some loss of jobs.	3.81 (0.084)
3. It is the government's responsibility to impose high taxes(on fossil fuels.	3.45 (0.097)
4. The US government should impose stricter laws on pollution.	3.97 (0.087)
5. People should pay higher prices to address climate change.	3.19 (0.096)
6. There should be more investment using tax dollars in alternative fuels.	3.80 (0.092)
7. People should make lifestyle changes to reduce environmental damage.	4.20 (0.074)
8. It is important to purchase things that are more environmentally friendly, even at a greater cost.	3.74 (0.083)
9. 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)
10. Personal food choices can affect the environmental impact of agriculture.	3.96 (0.081)
Environmental score	38.01 (0.720)

sum of assigned values for all statements. This way, the environmental score has a minimum value of 10 if a respondent strongly disagrees with all 10 of the environmental statements and a maximum of 50 if the respondent strongly agrees with all of the same 10 statements. Table 8.3 shows that the average environmental score among all respondents is 38.01.[14]

8.4 Empirical Strategy to Estimate Willingness to Pay for Product Attributes

To analyze the impact of information on consumer choice, we define information provision via labels as an additional or differentiated product attribute. Recognizing that products can be defined as a bundle of perceived attributes provides the framework to compute consumers' willingness to pay for product attributes in a discrete choice model. Starting from a random utility framework (as in McFadden 1974, McFadden and Train 2000, and

14. The bottom right panel of figure 8A.2 shows that the average environmental score is balanced for the treatment and control groups, and given the confidence intervals, we cannot reject that the averages are similar. Furthermore, when comparing the full distributions in the top left panel of figure 8A.3 using kernel density estimates and in a Kolmogorov Smirnov equality of distributions test, a p-value of 0.943 implies that we cannot reject the null of equal distributions for the environmental score of respondents in the treatment and control groups.

Train 2003), where both the product attributes as well as the random term are assumed to enter linearly, the utility from consuming a certain product can be described as

$$U_{ji} = X_j \beta_i + \varepsilon_{ji}. \tag{1}$$

The matrix X_j indicates the attributes of product j, the vector β_i indicates the marginal utility that individual i places on these attributes, and ε_{ji} indicates the error term.

Distributional assumptions about β_i and ε_{ij} drive the econometric model decision. If we assume that ε_{ij} is independently and identically distributed extreme value (type I), then we have a logit choice model. If we also specify

$$\beta_i = \beta_0 + \beta_1 D_i, \tag{2}$$

then we have a mixed logit model, where the marginal utility coefficients vary according to the respondent's observed demographics D_i. This implies that different decision-makers may have different preferences. If instead we allow decision-makers to have different preferences due to a more general unobserved heterogeneity structure, and not just due to observable demographics, then we define the coefficients β_i to vary as

$$\beta_i = \beta_0 + \beta_2 v_i, \tag{3}$$

where v_i is a normal random variable capturing any heterogeneity. If there is no heterogeneity in individual preferences relative to the average, then β_2 will be zero. If, however, there is heterogeneity in preferences relative to the average, then β_2 will be different from zero. If β_i is specified as (3), then we have a random coefficient logit model. This offers flexibility in incorporating consumer heterogeneity with regard to food choice attributes, such as organic and low water footprint.[15]

Third, if we define the coefficients β_i to be combination of the two previous heterogeneity specifications as

$$\beta_i = \beta_0 + \beta_1 D_i + \beta_2 v_i, \tag{4}$$

we have a random coefficients mixed logit model with demographics as mixing parameters. If there is no heterogeneity in individual preferences relative to the average, then β_1 and β_2 will be zero. If, however, there is heterogeneity in preferences due to demographics relative to the average, then β_1 will be different from zero, and if there is additional random heterogeneity, then β_2 will be different from zero as well. This choice model offers flexibility in incorporating consumer heterogeneity with regard to food attributes as a function of D_i directly as well as allowing for random determinants of heterogeneity via v_i. This modeling approach combined with the unique choice experimental

15. To recover how D_i affects the departure from mean valuations, we project estimated β_i on observed demographics D_i in a second step.

setting and resulting data variation for agricultural food choices allows us to estimate consumers' valuation for water efficiency on average together with the complete distribution of valuation of survey respondents (as in Revelt and Train 2000 and Huber and Train 2001).[16]

Assuming that consumers choose one unit of product j among all the possible products available at a certain time that maximizes their indirect utility, then the probability that good j is chosen is the probability that good j maximizes consumer i's utility

$$\text{(5)} \quad \Pr(\text{Choice}_j) = \Pr(U_{ji} > U_{ki}) = \Pr(X_j\beta_i + \varepsilon_{ji} > X_k\beta_i + \varepsilon_{ki}), \forall k \neq j.$$

Then the following closed-form solution can be derived for the probability that a respondent's product choice corresponds to product j as

$$\text{(6)} \qquad Prob_{ji} = \frac{e^{X_j\beta_i + \alpha\,\text{Price}_j}}{\sum_{k=0}^{N} e^{X_k\beta_i + \alpha\,\text{Price}_k}},$$

where $\alpha = \alpha_0$ is the marginal utility with respect to price, which is constant for all respondents, and β_i contains the marginal utilities relative to the remaining attributes X for respondent i. The mean utility of the option "I would not purchase any of these" presented to a respondent in the choice experiments is normalized to zero. In other words, the organic, LWF, and price variables for the outside option is set equal to zero in all the experimental choice cases. This implies that equation (6) becomes

$$\text{(7)} \qquad Prob_{ji} = \frac{e^{X_j\beta_i + \alpha\,\text{Price}_j}}{1 + \sum_{k=1}^{N} e^{X_k\beta_i + \alpha\,\text{Price}_k}}.$$

Finally, given that each respondent makes decisions for the four different products, defining $T = 4$ products and defining the distribution of the $\theta = (\alpha,\beta)$ parameters in general form as $f(\theta\,|\,\alpha_0,\beta_0,\beta_1,\beta_2)$, where β is specified in equations (2), (3), or (4) and $\alpha = \alpha_0$ for all respondents, then the probability of individual i making a sequence of choices among the five alternatives $(j = 0, \ldots 4)$ is given as

$$\text{(8)} \qquad S_i = \int \prod_{t=1}^{T} \prod_{j=0}^{4} \left[\frac{e^{X_{ijt}\beta_i + \alpha\text{Price}_{jt}}}{1 + \sum_{k=1}^{N} e^{X_{ikt}\beta_i + \alpha\text{Price}_{kt}}} \right]^{Y_{ijt}} f(\theta\,|\,\alpha 0,\beta_0,\beta_1,\beta_2)\,d\theta,$$

where $Y_{ijt} = 1$ if the respondent i chooses alternative j for situation t and 0 otherwise. Given a total of I respondents, the parameters $(\alpha = \alpha_0,\beta_0,\beta_1,\beta_2)$ are estimated by maximizing the simulated log-likelihood function

$$\text{(9)} \qquad SLL = \sum_{i=1}^{I} \ln\left(\frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=0}^{4} \left[\frac{e^{X_{ijt}\beta_i^{[r]} + \alpha\text{Price}_{jt}}}{1 + \sum_{k=1}^{N} e^{X_{ikt}\beta_i^{[r]} + \alpha\text{Price}_{kt}}} \right]^{Y_{ijt}} \right),$$

where $\beta_i^{[r]}$ is the r-th draw for respondent i from the distribution of β.

16. To recover how D_i affects the departure from mean valuations, we project estimated β_i on observed demographics D_i in a second step.

8.4.1 Estimating Average and Heterogeneous Marginal Utility and Willingness to Pay

To estimate β_i, we proceed as follows. Given that the expected value of β, conditional on a given response Y_i of individual i and a set of alternatives characterized by X_i for product t, is given by

$$(10)\quad E[\beta \mid Y_i, X_i] = \frac{\int \beta \prod_{t=1}^{T} \prod_{j=0}^{4} \left[\left(e^{X_{ijt}\beta + \alpha \text{Price}_{jt}} \right) \Big/ \left(1 + \sum_{k=1}^{N} e^{X_{ikt}\beta + \alpha \text{Price}_{kt}} \right) \right]^{Y_{ijt}} f(\beta \mid \beta_0, \beta_1, \beta_2) d\beta}{\int \beta \prod_{t=1}^{T} \prod_{j=0}^{4} \left[\left(e^{X_{ijt}\beta + \alpha \text{Price}_{jt}} \right) \Big/ \left(1 + \sum_{k=1}^{N} e^{X_{ikt}\beta + \alpha \text{Price}_{kt}} \right) \right]^{Y_{ijt}} f(\beta \mid \beta_0, \beta_1, \beta_2) d\beta},$$

then equation (9) can be thought of as the conditional average of the coefficient for the subgroup of individuals who face the same alternatives and make the same choices. For each individual i, we estimate a certain attribute's β_i, following Revelt and Train (2000), by simulation according to the following

$$(11)\quad \hat{\beta}_i = \frac{(1/R) \sum_{r=1}^{R} \beta_i^{[r]} \prod_{t=1}^{T} \prod_{j=0}^{4} \left[\left(e^{X_{ijt}\beta_i^{[r]} + \alpha \text{Price}_{jt}} \right) \Big/ \left(1 + \sum_{k=1}^{N} e^{X_{ikt}\beta_i^{[r]} + \alpha \text{Price}_{kt}} \right) \right]^{Y_{ijt}}}{(1/R) \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=0}^{4} \left[\left(e^{X_{ijt}\beta_i^{[r]} + \alpha \text{Price}_{jt}} \right) \Big/ \left(1 + \sum_{k=1}^{N} e^{X_{ikt}\beta_i^{[r]} + \alpha \text{Price}_{kt}} \right) \right]^{Y_{ijt}}},$$

where $\beta[r]$ is the r-th draw for individual i from the estimated i's distribution of β.

The resulting estimates of each respondent's WTP for a particular attribute x are obtained as the ratio of β_i and the marginal utility with respect to price α. We can therefore recover not just the average WTP but also the distribution of the WTP in the sample of respondents, and standard errors are obtained using the Delta Method. Finally, we relate the estimated willingness to pay (WTP_i) to each respondent's demographics and environmental scores by estimating the equation

$$(12)\qquad WTP_i = \gamma_0 + \gamma_1 D_i + \varepsilon_i^w,$$

where WTP_i is a vector of all respondents' individually estimated willingness to pay for the LWF alternatives, D_i are the demographic characteristics (including the environmental score) of respondent i, and γ_0, γ_1 are parameters to be estimated.

8.5 Results

First we present the results from the choice estimates originating from a conditional logit specification. In this first step, we investigate whether there is significant average stated marginal utility for LWF options as well as stated heterogeneity in the marginal utility as a function of observable characteristics of the respondents in terms of demographics and environmental score. Second, we explore a more flexible random coefficients choice model, allowing the heterogeneity to vary from the average marginal utility in a random fashion. Third, we include D_i as mixing parameters directly and estimate the random coefficients mixed logit model. Given that the conditional logit, as well as the random coefficient logit and the random coefficient mixed logit models, is estimated by maximizing the likelihood and simulated likelihood, respectively, we perform model comparisons using the Akaike information criterion (AIC) among the estimated specifications and discuss the best specification used moving forward.

The average marginal utility as well as each respondents' marginal utility are estimated using simulated maximum likelihood (Revelt and Train 2000). The intuition behind the estimation is that each respondent's β_i is computed as a conditional average of the βs of respondents similar to them, in that they make similar sequences of choices when presented with the same options in the experimental design and have similar demographics D_i. Each respondent's WTP for the LWF attribute is then obtained as the ratio between the β_i and the marginal utility of price α.

The variation in estimated individual departures from the average WTP can be either purely random or due to the fact that respondents have similar characteristics. This is investigated by correlating the estimated WTP_i with respondents' demographics and environmental scores.

8.5.1 Conditional Logit Estimates

In table 8.4, we present the estimates of the conditional logit choice model specification, where β_i are given by equation (2). The dependent variable in all of the columns is an indicator variable that is equal to one if an individual chose that alternative and equal to zero otherwise. There are five alternatives to choose from in each of four product groups. All specifications include individual fixed effects controlling for constant characteristics that may affect their choice behavior on average as well as product fixed effects to control constant characteristics of each agricultural product.

In column (1), the right-hand-side variables are the price, an "Organic" dummy that is equal to one if the alternative is organic and equal to zero otherwise, an indicator *LWF* equal to one for if the alternative has a low water footprint and equal to zero otherwise, and interactions *Treat* × *Organic* and *Treat* × *LWF*, where Treat is equal to one if the respondent was in the information treatment group. From the estimates in column (1), we see that the coefficient on price is negative and significant, meaning that a high price lowers the marginal utility of purchasing an alternative. The marginal utility of the organic attribute is negative but not significantly different from zero. The LWF attribute has an average marginal utility of 1.272, which is positive and significant. Finally, while being in the treatment group does not imply a higher marginal utility for the LWF attribute, given the nonsignificant coefficient of the interaction *Treat* × *LWF*, being in the treatment group implies a significantly lower marginal utility for the organic attribute, given the negative and significant coefficient of the interaction *Treat* × *Organic*.

Table 8.4 **Conditional logit choice estimates**

	Condit. logit (1)	Condit. logit (2)
Price	–0.139***	–0.146***
	(0.019)	(0.020)
Organic	–0.164	–0.152
	(0.120)	(0.123)
LWF	1.272***	–2.382***
	(0.109)	(0.440)
Treat × LWF	0.179	0.297*
	(0.148)	(0.161)
Treat × Organic	–0.297*	–0.285*
	(0.160)	(0.164)
Env × LWF		0.053***
		(0.008)
Edu × LWF		0.430***
		(0.108)
White × LWF		0.690***
		(0.188)
No. of obs.	4160	3,960
Log likelihood	–1,168.959	–1,074.598
AIC	2,347.919	2,165.195
Product FE	Yes	Yes
Respondent FE	Yes	Yes

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table displays the estimates of conditional logit regressions where the dependent variable is equal to one if an alternative out of 5 is chosen and equal to zero otherwise. *Organic* = 1 for organic choices. *LWF* = 1 for low water footprint choices—that is, the more efficient characteristic. *Treat* = 1 if the respondent received the information treatment. Specification (2) also includes the interaction of *LWF* and respondent characteristics. Only the significant coefficients are reported due to space in column (2). Respondents' AIC reports the Akaike's information criterion for model specification testing.

In column (2), we further interact demographic characteristics such as age, income, education, gender, and environmental score with the variables in column (1). This specification in column (2) allows us to estimate the average marginal utility for all variables in column (1) as well as departures from those averages with respect to the observable characteristics of the respondents. Even though all the lower-order terms of triple interactions are included in the specification in column (2), they are not all reported in table 8.4 due to space limitations. The number of observations drops in column (2) because not all respondents gave us complete demographic information.

First, we find that the log likelihood increases to −1075, relative to −1169 in column (1), implying that we explain more of the variation in choices with this specification. Moreover, when comparing models, the second specification is preferred, given its lower AIC estimate. Second, the marginal utility of price remains negative and significant. Third, there is heterogeneity for the LWF attribute in specification (2) that the averages in (1) mask, given that several coefficients associated with the interaction of demographics and product attributes are statistically different from zero. In particular, the marginal utility for the LWF attribute increases significantly with the environmental score (given the positive and significant coefficient of 0.053), increases with education (coefficient of 0.430), and increases for white respondents (coefficient of 0.690). None of the other demographics significantly affect the marginal utility with respect to the LWF attribute. Fourth, there is no organic marginal utility heterogeneity. Finally, none of the triple interactions terms, such as $Treat \times LWF \times D_i$, are significant for any D_i. This implies that there is no differential heterogeneity in the treatment group and in the control group in the way respondents value organic or low water footprint options depending on their observable demographics and environmental score.

We next turn to a mixed logit specification—a more flexible choice specification where we allow the average taste parameters to vary randomly for the respondents and not just as a function of a set of observable respondents' characteristics. We also compare the log likelihood of these nested model specifications and test whether conditioning on demographics or allowing for random heterogeneity explains more of the observed variation in the choices of different consumers when faced with the choice experiment design.

8.5.2 Random Coefficients Logit Choice Estimates

In the first two columns of table 8.5, we present the estimates of the random coefficients logit choice model specification, where β_i are given by equation (3). The dependent variable in all of the columns is an indicator variable that is equal to one if an individual chose that alternative and equal to zero otherwise. There are five alternatives to choose from in each of four product groups. All specifications include respondent fixed effects controlling for constant characteristics that may affect their choice behavior on average. In columns (1) and (2), the right-hand-side variables are the same as in column (1) of table 8.4; however, in column (1), we allow for unobserved random heterogeneity in the two product attributes *LWF* and *Organic*, and in column (2), we additionally allow the information treatment parameters to have random unobserved heterogeneity by estimating a random coefficient for $Treat \times LWF$ and $Treat \times Organic$.

The top half of table 8.5 (labeled "Mean") reports the average estimated marginal utilities. The price coefficient is negative and significant in columns (1) and (2) of table 8.5 and in the same magnitude of the marginal utility estimates of price for the conditional logit specifications in table 8.4. From the estimates in column (1), we see that the coefficient of price is negative and

Table 8.5 **Random coefficient and mixed logit choice estimates**

	Random coeff. logit (1)	Random coeff. logit (2)	Mixed logit (3)
Mean			
Price	–0.191***	–0.191***	–0.194***
	(0.023)	(0.023)	(0.024)
Organic	–0.683**	–0.637**	–0.685**
	(0.305)	(0.301)	(0.317)
LWF	1.546***	1.516***	–2.735***
	(0.191)	(0.179)	(0.674)
Treat × Organic	–0.518	–0.646	–0.665
	(0.421)	(0.492)	(0.505)
Treat × LWF	0.252	0.325	0.391
	(0.267)	(0.281)	(0.255)
Env × LWF			0.058***
			(0.013)
Edu × LWF			0.521***
			(0.169)
White × LWF		a	0.822***
			(0.299)
SD			
LWF	1.427***	1.250***	0.998***
	(0.174)	(0.223)	(0.212)
Organic	2.409***	2.270***	2.362***
	(0.279)	(0.345)	(0.349)
Treat × Organic		1.197	1.316
		(1.014)	(0.957)
Treat × LWF		1.088**	0.841*
		(0.513)	(0.465)
No. of obs.	4,160	4,160	3,960
Log likelihood	–1,059.665	–1,058.920	–983.592
AIC	2,133.329	2,135.841	1,991.184
Respondent FE	Yes	Yes	

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table displays the estimates of mixed logit regressions where the dependent variable is equal to one if an alternative out of 5 is chosen and equal to zero otherwise. *Organic* = 1 for organic choices. *LWF* = 1 for low water footprint choices. *Treat* = 1 if the respondent received the information treatment. AIC reports the Akaike's information criterion for model specification testing.

significant, meaning that a high price lowers the marginal utility of purchasing an alternative. The average marginal utility of the organic attribute is negative and significant. The LWF attribute has an average marginal utility that is positive and significant. Finally, being in the treatment group does not imply a higher marginal utility for the LWF attribute nor for the organic attribute, given the nonsignificant coefficients of the interactions *Treat* × *LWF* and *Treat* × *Organic*.

The bottom half of table 8.5 (labeled "SD") reports the standard errors of estimated marginal utilities. There is significant heterogeneity in the marginal utility of the two attributes, given the significant and positive coefficients for the standard errors of the LWF and organic marginal utilities.

8.5.3 Random Coefficients Mixed Logit Choice Estimates

Next, we investigate whether a random coefficient mixed logit presents itself as the preferred specification to move forward in estimating WTP and performing policy simulations. In the third column of table 8.5, we present the estimates of the random coefficients mixed logit choice model specification, where β_i are given by equation (4). In addition to the random coefficients in column (2), in column (3) we additionally allow the demographic characteristics and environmental score to interact with the *LWF*, choosing the interactions that yielded significant coefficients in the conditional logit specification in table 8.4.

For the mean marginal utilities in column (3), the price coefficient is negative and significant and in the same magnitude of the marginal utility estimates of price for the random coefficients logit in columns (1) and (2) as well as in the same magnitude as the conditional logit specifications in table 8.4. As we would expect, this means that a higher price lowers the marginal utility of purchasing an alternative. The mean marginal utility of the organic attribute is negative and significant. The *LWF* attribute has an average marginal utility of −2.735, which is negative and significant and is different from the point estimates in column (1) and (2), since now the *LWF* attribute is interacted with demographics. To get the average marginal utility for the *LWF* attribute we need to add the mean coefficient of −2.735 to the coefficient of the demographic interactions times the average demographics, which we do later.

Finally, being in the treatment group does not imply a higher mean marginal utility for the LWF or Organic attribute, given the nonsignificant coefficients of the interactions *Treat* × *LWF* and *Treat* × *Organic*. One possible reason the information treatment about the drought was ineffective is that California residents were already aware of the severity of the highly publicized drought. According to Google trends, web searches for the phrase "California drought" in California have been high since the beginning of 2014.[17] Providing additional information that consumers already consider when faced with a low water footprint label would not lead to a behavioral response.

Looking at the deviations from the mean marginal utilities, reported in the bottom of table 8.5 under the label "SD," there is significant heterogeneity in the marginal utility of the two attributes. This is evidenced by the positive and significant estimates of standard deviations of the LWF and organic marginal utilities.

17. Source: Google Trends, "California Drought" web searches, accessed April 28, 2017, https://www.google.com/trends/explore?geo=US-CA q=california%20drought.

To interpret the point estimates for the attribute of interest, we obtain the mean marginal utility for the LWF attribute by adding up the mean marginal utility of −2.735 with the heterogeneous marginal utilities estimated by interactions with demographics.[18] The sum of the average marginal utility and all the heterogeneity terms equals 1.78, an estimate that is larger but in the ballpark of the estimates in columns (1) and (2) of table 8.5.

Moving forward, we choose the model that better predicts the choices made by respondents in our sample using the AIC. The AIC is like a log likelihood ratio test with an extra adjustment in terms of number of regressors in the specifications for different models. When testing between models, we choose the model that has the lowest absolute value of the AIC. We compare all columns of tables 8.4 and 8.5 using the reported AIC. We choose column (3) of table 8.5 because it is the model that has the lowest AIC, equal to 984. In the remainder of this chapter, we will use this random coefficient mixed logit as the specification to estimate respondents' distribution of marginal utilities and the distribution of WTP and to perform counterfactual policy simulations.

8.5.4 Willingness to Pay for Low Water Footprint Attribute and Willingness to Pay for Gallons of Water Saved

Given the estimated model parameters in column (3) of table 8.5, we start by estimating the distribution of the respondents' individual marginal utilities and resulting WTP_i with respect to the attribute of interest.

Each individual β_i is estimated using equation (11) and then divided by the marginal utility of price α to obtain each WTP_i. The top left panel of figure 8.1 displays the kernel density of the distribution of WTP_i for the LWF attribute, and the top right panel breaks up the average estimated WTP for the white subgroup and the nonwhite subgroup. The two bottom panels relate estimated WTP to two demographic characteristics of the respondents.

We estimate that the average WTP is 11.02 dollars for the LWF attribute. Given that this attribute is associated with an average saving of 90.4 gallons, then the average WTP per gallon saved is 11.02/90.4, which is equal to 12 cents per gallon of water saved. In particular, we estimate the WTP to be 5.4 cents per gallon saved in the production of avocados, 9.3 cents per gallon saved in the production of almonds, 48 cents per gallon saved in the production of tomatoes, and 1.3 cents for one gallon of water saved in the production of lettuce.

Furthermore, the estimated distribution of WTP in the top left panel of figure 8.1 is not concentrated at the average WTP, suggesting that there

18. The heterogeneity part is equal to the marginal utility with respect to environmental score and LWF interaction (0.058) times the average environmental score (35.6) plus the marginal utility with respect to low water footprint and education (0.52) times the average education (3.5, recall that education is classified in increasing levels of school attained, from 1 to 4), plus the marginal utility for white and LWF (0.058) times the share of white respondents (77 percent).

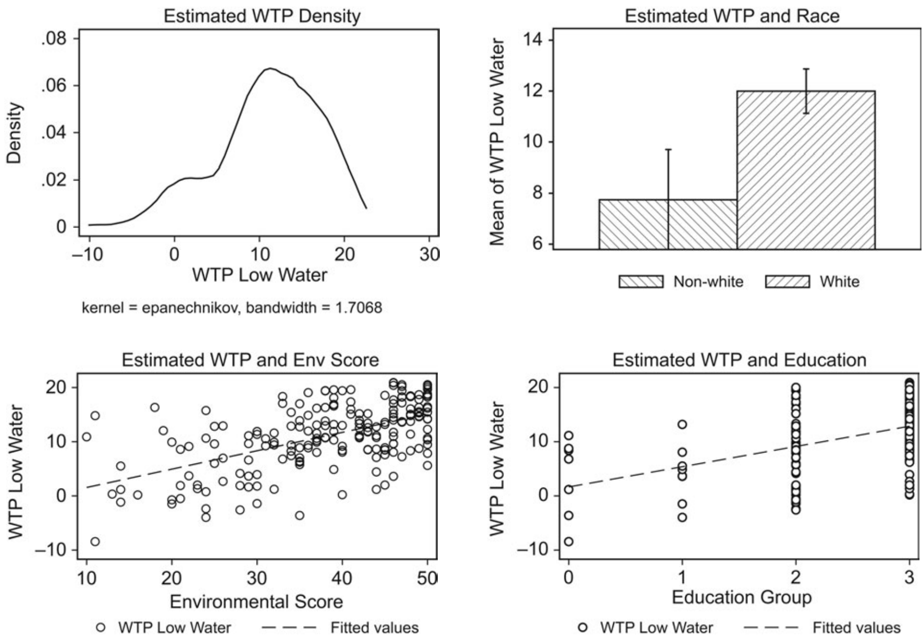

Fig. 8.1 Estimated WTP for low water attribute, for entire sample and by respondent characteristics

Notes: The figure displays the kernel density of the distribution of estimated WTP for the LWF attribute and then relates the estimated WTP for respondents to the respondents' demographics. Estimates are based on mixed logit choice specification with demographics and random coefficients. Education is considered in four ranges: education = 1 if "less than high school degree," education = 2 if "high school degree or equivalent (e.g., GED)," education = 3 if "some college but no degree or associate degree," and finally, education = 4 if "bachelor degree or graduate degree."

is heterogeneity in the value of the LWF attribute. Looking first into race, breaking up the WTP by white and nonwhite subgroups of respondents, does render significant differences in WTP, as we can see in the right panel of figure 8.1, where the average for white respondents is higher than for nonwhite respondents. Illustrative evidence in the two bottom panels of figure 8.1 suggests that there is a positive relationship between the respondents' estimated WTP and the environmental score of respondents as well as a positive relationship between the estimated WTP and the respondents' increasing degree of education attained. When sorting individuals by increasing environmental score on the horizontal axis, we fit an upward sloping linear OLS model estimate from regressing WTP and environmental score, as depicted by the fitted values in the upward sloping line in the bottom left panel of figure 8.1. The same happens for the scatter plot of WTP and education levels as shown in the bottom right panel data scatter plot and upward sloping linear fitted values.

Heterogeneity in the WTP is formally investigated by estimating equation

Table 8.6 **Regression of respondents' mixed logit WTP estimates on demographics**

	WTP for LWF characteristic (1)
Env.	0.304***
	(0.037)
Income	0.195
	(0.289)
Educ.	2.403***
	(0.465)
Age	–0.078
	(0.218)
Female	0.709
	(0.623)
White	4.277***
	(0.739)
Constant	–12.814***
	(1.610)
No. of obs.	193
R-squared	0.530

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(12), a linear regression of the estimated individual WTP, and the characteristics of the respondents. The estimates are reported in table 8.6. While income, age, and gender are not significantly correlated with the WTP for the low water option, a respondent's stated level of education and environmental score are both positively correlated with WTP. The white subgroup of the respondents also has a significantly higher WTP than their nonwhite counterparts.

8.6 Choice Changes and Welfare Changes in Counterfactual Policy Simulations

Finally, we ask the counterfactual question of what would happen to respondents' choices and consumer welfare, ceteris paribus, were there to be no water footprint information revealed to consumers. To answer this question, we perform simulations and compute the maximizing utility choices for each respondent in this counterfactual scenario. With that, we are able to simulate respondents' new choices and estimate the distribution of changes in respondents' consumer surplus. To assess who loses and who wins, we project the changes in consumer surplus on respondents' demographics and environmental scores in the final step.

8.6.1 Simulating Respondents Counterfactual Choices

For each counterfactual scenario, we keep respondents' preferences unchanged, which in practice means that the marginal utility parameters are not changing from the baseline model presimulation. To estimate choices given the model parameters, we estimate the probabilities of each attribute being chosen in each product (avocados, almonds, lettuce, and tomatoes) by all respondents, given the data on the attributes presimulation as in equation (7). In so doing, we obtain the predicted presimulation baseline choices for all respondents. Then we change the vector or vectors of attributes under the counterfactual scenario considered, defined as $\tilde{X}$, and recompute the probabilities that each respondent would make under this scenario for all cases, using the new attributes in equation (7). For example, simulating no low water footprint labels means that all products are indistinguishable in this counterfactual scenario along the LWF attribute, which means in practice that $X_{ij,LWF} = 0, \forall i, j$, which also implies that all interactions with that attribute are zero in the scenario.

8.6.2 Estimating Consumer Welfare Changes in Policy Simulations

Estimates of changes in consumer surplus (CS) are derived through simulation of consumer choices under counterfactual compositions of their attribute choice sets. These correspond to a respondent's compensating variation for a change in product attributes (Small and Rosen 1981). The expected consumer surplus, CS_i, is defined as

$$CS_i = \frac{1}{\alpha} \ln \sum_j e^{X_j \beta_i - \alpha Price_j}, \tag{13}$$

where α denotes the marginal utility of price. We estimate the consumer surplus for the choices as they are and for the best alternative when the LWF attribute is removed and when there is no longer a drought information treatment. Changes in consumer surplus are then obtained for each respondent. We estimate the average change in consumer surplus as well as how changes in consumer surplus are related to respondents' individual demographic characteristics and environmental score by estimating the following equation

$$\Delta(CS)_i = \delta_0 + \delta_1 D_i + \varepsilon_i^{cs}, \tag{14}$$

where $\Delta(CS)_i$ is a vector of all the respondents' individually estimated changes in CS for the policy simulation of no drought information and no LWF label, D_i are the demographic characteristics (including the environmental score) of respondent i, and δ_0, δ_1 are parameters to be estimated.

8.6.3 Policy Simulation of Removing Low Water Footprint and Drought Information

First, we estimate the predicted average probabilities of the choices for each of the five alternatives given the estimated parameters of column (3) in table 8.5. These are depicted in the left panel of figure 8.2 with the confidence intervals for each alternative. Recall that alternative 1 (A1) is the conventional and average water footprint option, alternative 2 (A2) is conventional and low water footprint, alternative 3 (A3) is organic and average water footprint, alternative 4 (A4) is organic and low water footprint, and alternative 5 (A5) is none of the above.

In the baseline, all the average predicted probabilities are statistically significantly different from each as given by the confidence intervals in figure 8.2. The option most chosen, as predicted by the model, is A2 (conventional and LWF). The next option is A4 (organic and LWF). The third most chosen is the outside option, A5 (none of the above). The least chosen option is A3 (organic and average water footprint).

When simulating the counterfactual choices of removing the LWF labels from the information set of the respondents, the average predicted probabilities change significantly relative to the baseline, as given by the right panel of figure 8.2. Now the most chosen option is not to select any of the four options—namely, A5. A2 and A4 (the LWF options) drop significantly relative to baseline. A3's probability of being chosen is now significantly different from zero, as respondents switched from A4 toward A3. This is because both A3 and A4 are organic, A3 is cheaper than A4, and now there is no reason to buy A4, given that the LWF label is not available as differentiation. The same happens for A1 and A2—A2 drops relative to baseline and A1 increases, as A1 is cheaper than A2 and both are conventional products. In terms of welfare, since the outside option increases so much and its utility is normalized to zero, it is expected that those consumers who switch to A5 have a lower utility than before.[19] We investigate formally the changes in respondents' consumer surplus by comparing the baseline and the counterfactual scenario's compensated variation for all respondents.

Figure 8.3 presents the estimated changes in consumer surplus for the respondents when they are faced with the same five options, but A2 and A4 are no longer identified as low water footprint, and they are no longer given an information treatment on the drought. The top left panel of this figure depicts the kernel density of the distribution of changes in consumer surplus for all respondents. Most of the consumers lose, given that most of the mass is below 0, some respondents stay the same, while a small proportion of the distribution covers positive welfare changes. Overall, the visual evidence suggests that this policy experiment has a net welfare loss.

In the remaining panels of figure 8.3, we relate the changes in simulated consumer surplus to respondents' characteristics. The top right panel shows an almost flat but slightly negative fitted linear regression of changes in consumer surplus with respondents' environmental scores. In the left bottom panel, it appears that the average change in consumer surplus is more negative for lower educated subgroups than for higher educated subgroups, although those differences are not statistically different from each other. In

19. All products exhibit similar changes in probabilities.

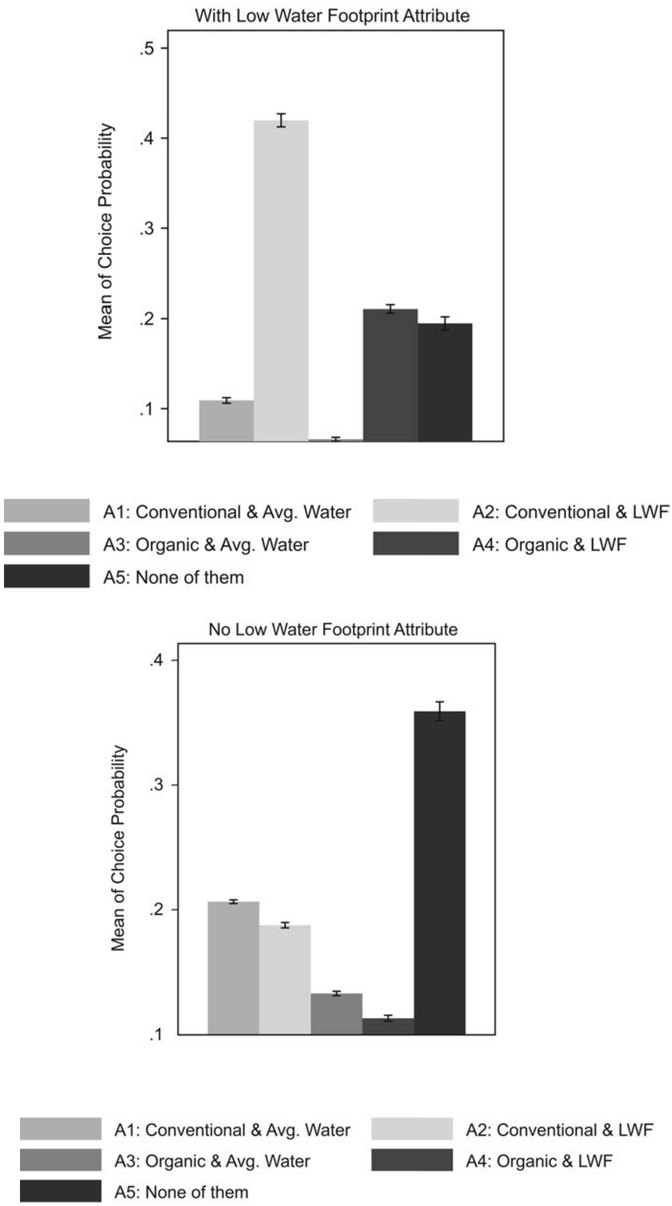

Fig. 8.2 Estimated probability of choosing an alternative, with and without a low water footprint attribute

Notes: The figure displays the average estimated probabilities, and confidence intervals, of choosing the five alternatives with and without an LWF attribute. Estimates are based on the random coefficients mixed logit choice specification with demographics and random coefficients. The five alternatives are (1) conventional and average water, (2) conventional and low water, (3) organic and average water, (4) organic and low water, and (5) none of them.

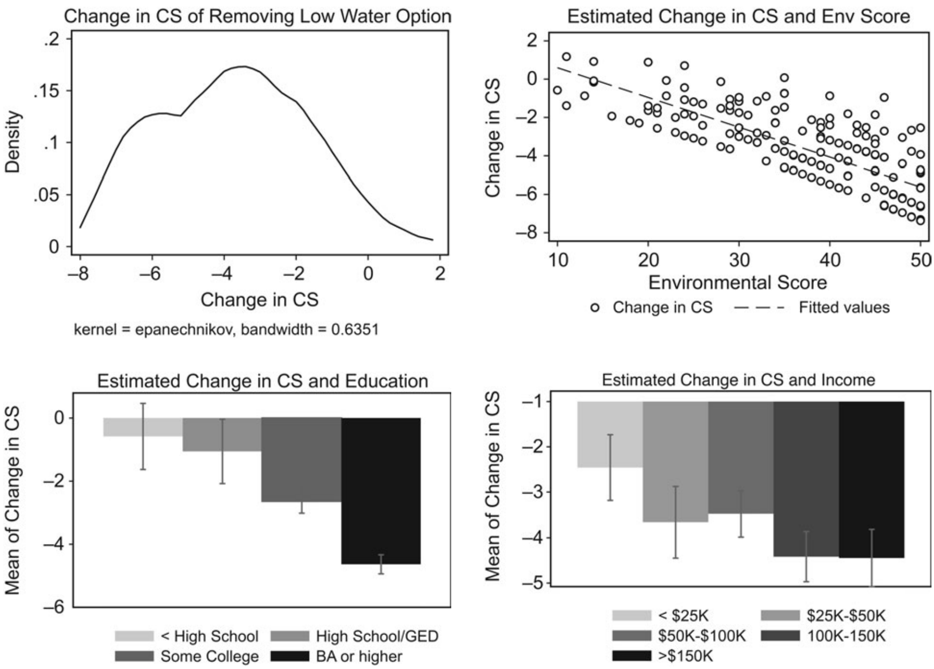

Fig. 8.3 Estimated change in consumer surplus with and without a low water attribute

Notes: The figure displays the kernel density of the distribution of changes in CS with and without the LWF attribute. Estimates are based on mixed logit choice specification. Education is considered in four ranges: less than high school degree, high school degree or equivalent (e.g., GED), some college or associate degree, and bachelor degree or graduate degree. Income is classified into five ranges: less than $25,000, $25,000–49,999, $50,000–$99,999, $100,000–149,999, and $150,000 or more.

the bottom right, we also see a nonlinear relationship between respondents' income and respondents' average change in consumer surplus.

We test whether there are significant heterogeneous changes in consumer surplus by estimating equation (12). These estimates are reported in table 8.7. On average, respondents lose 3.35 dollars in terms of surplus from this policy experiment. Given that the average price of the chosen option is about 3 dollars, this is a large loss and corresponds to the most action being driven by consumers who switch to the outside option of not consuming anything. The findings in table 8.7 are consistent with the graphical correlations in the top right and bottom panels of figure 8.3. Higher education and being white are negatively and significantly correlated with consumer surplus losses. A higher environmental score is correlated with a larger consumer surplus loss, although the negative point estimate is economically very small and not significant. Respondents' income is uncorrelated with consumer surplus losses, given the insignificant coefficient associated with increases in income.

Table 8.7 Regression of change in consumer surplus estimates on demographics

	Change in CS (1)
Env.	–0.142*** (0.005)
Income	–0.012 (0.032)
Educ.	–1.057*** (0.091)
Age	–0.042 (0.034)
Female	–0.036 (0.097)
White	–1.933*** (0.128)
Constant	7.045*** (0.470)
Num. of obs.	193
R-squared	0.929

Note: Change in consumer estimates from simulation of removing LWF option. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

From the top left panel of figure 8.3, we identify a large proportion of respondents who lose and also a smaller proportion of respondents who do not lose in this policy experiment. To understand this heterogeneity, figure 8.4 breaks up the baseline choices (top panels) and simulated predicted choices (bottom panels) for those who have a net loss (left panels) and for those who do not (right panels). We can now see that the ones who have no welfare losses (right panels) were those respondents whose preferred alternative was A5 (i.e., none of them), then A1 and A3, and lastly A2 and A4, which are the LWF options. It is therefore not surprising that welfare does not drop for these consumers due to the policy. Welfare actually increases slightly for these respondents due to random factors affecting utility. In the left panels, the net losers were those consumers who preferred A2 and A4 and due to the policy had the largest inconvenience and had to make significantly different choices from the top left to the bottom left panel.

Finally, we estimate that total welfare drops, given that the sum of changes in consumer surplus is −749.2 for the losers and 3.77 for the nonlosers in the survey sample. Given that the sample is more educated, has higher income, and is more white than the California average, and because we find greater consumer surplus losses for those who are white, educated, and wealthier, we may be overestimating the welfare losses in California. We reweight each consumer surplus change estimate to reflect the California distribution of income, race, and education and recompute the total change in the reweighted change in consumer surplus. The histogram of changes in consumer surplus for the survey sample (dark bars) and the histogram of

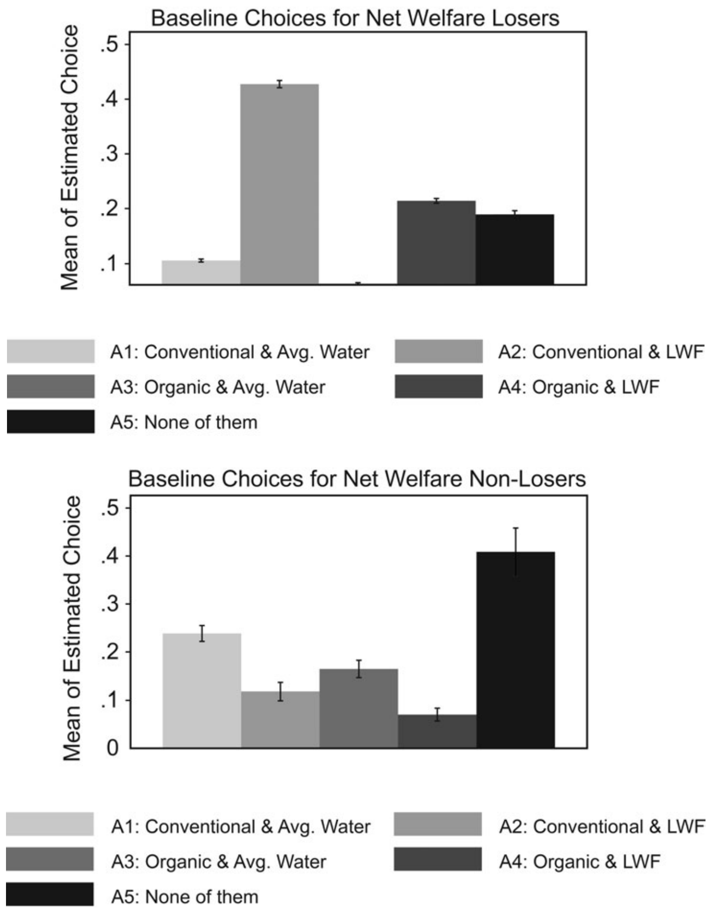

Fig. 8.4 Estimated probability of choosing alternatives, with and without a low water attribute and for net welfare losers and nonlosers

Notes: The figure displays the average estimated probabilities, and confidence intervals, of choosing the five alternatives with the LWF attribute (baseline top panels) and without LWF attribute (simulated bottom panels). Estimates are based on the random coefficients mixed logit choice specification for net welfare losers (left panels) and nonlosers (right panels). The five alternatives are (1) conventional and average water, (2) conventional and low water, (3) organic and average water, (4) organic and low water, and (5) none of them.

changes in consumer surplus for the reweighted California (light bars) are depicted in figure 8.5. We see that most of the mass of the reweighted histograms for income (top left), education (top right), age (bottom left), and race (bottom right) shifts to the right, meaning that the sample was indeed overstating the welfare losses relative to the CA population. We obtain a total net loss of −237 dollars when reweighting by income, −268 when reweighting by education, −323 when reweighting by age, and −415 when reweighting to match the race distribution in California. While these are all lower estimates

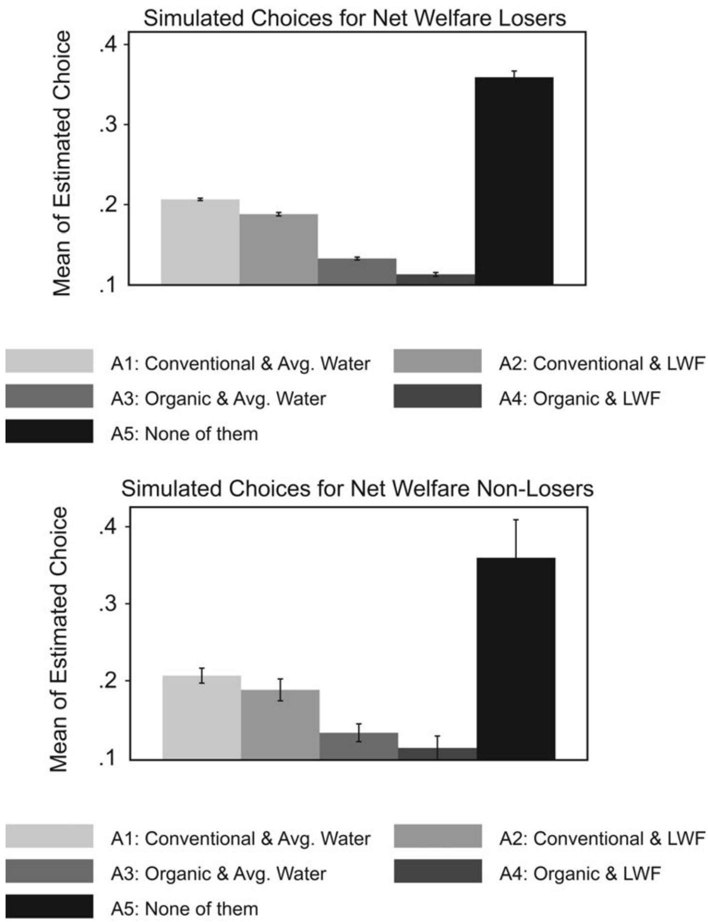

Fig. 8.4 (cont.)

of welfare losses than the sample estimate of −745, they are significantly different than zero.

8.7 Conclusion

In the context of recent California drought years, we investigate empirically whether consumers are willing to pay for more efficient water usage in the production of four California agricultural products. We implement an Internet survey choice experiment for avocados, almonds, lettuce, and tomatoes to elicit consumer valuation for water efficiency via revealed choices. We estimate a model of consumer demand where a product is defined as a bundle of three attributes: price, production method (conventional or

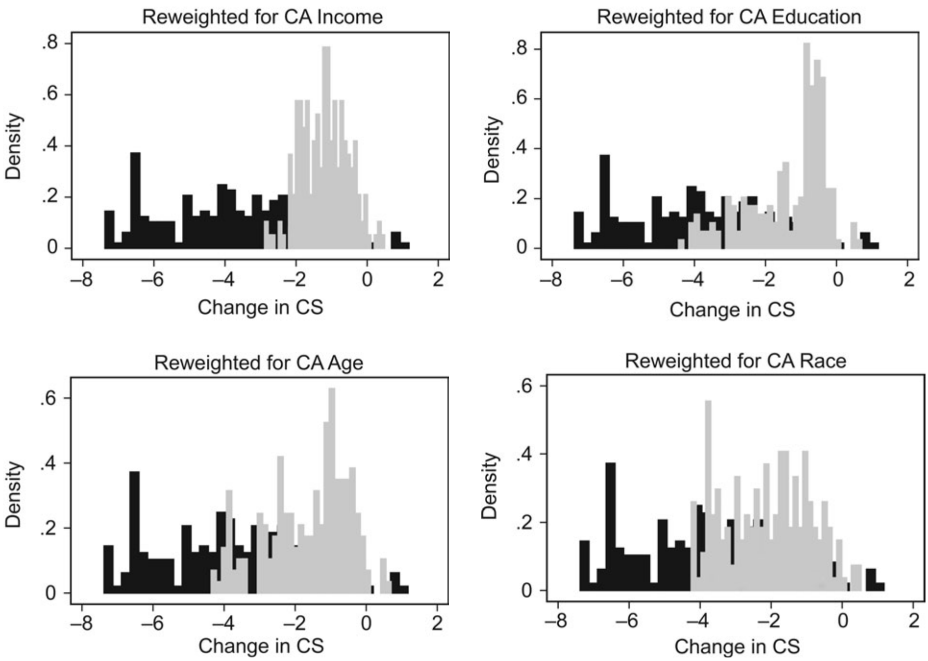

Fig. 8.5 Histograms of changes in consumer surplus for the survey sample (dark bars) and for the survey sample reweighted to the California distribution of demographics (light bars)

Notes: The figure displays the sample histogram of the respondents' changes in consumer surplus due to the counterfactual simulation of removing the LWF option, depicted with dark bars. In the light bars, we overlap the histogram of the estimated changes in consumer surplus where we reweight the sample to match the California distribution of income (top left), education (top right), age (bottom left), and race (bottom right), based on the random coefficients mixed logit choice specification. Estimates are based on mixed logit choice specification.

organic), and water usage (average or efficient). Varying the attribute space presented to consumers in the experimental choice design gives us the data variation to estimate a discrete choice model based on a conditional logit specification and a random coefficient mixed logit specification. In so doing, this chapter provides researchers and policymakers with the first estimates of the distribution of WTP for low water footprint food options during drought years. In addition, we test whether revealing information on the drought matters for the WTP.

We find that, on average, there is an implied positive willingness to pay for water efficiency of about 11 dollars. In terms of gallons of water saved, this means that respondents are on average willing to pay 12 cents for each gallon of water saved in the production of food. Moreover, when informing consumers about the drought severity, this increases consumer's WTP for the LWF options, albeit not significantly. Having additional information on consumer demographic characteristics, we find that there is heterogeneity in the WTP along respondents' stated environmental concern. There is also significant heterogeneity with respect to education and race. Using counterfactual simulations of removing water footprint and drought information from the attribute choice set, we estimate changes in choices that imply significant consumer surplus losses, especially for respondents reporting higher levels of attained education and environmental score and for white respondents.

The consumer valuation estimates provide insights into the policy debate regarding how to label and present food products (Lee and Hatcher 2001) in California and in a future of water scarcity. The WTP far exceeds the cost of one gallon of water sold to agriculture, which ranges from 0.5 cents to 0.3 cents in California during drought years, 10 times as much as during nondrought years.[20] While a comprehensive cost-benefit analysis also requires data on the cost (possibly involving technological changes) of saving one gallon of water used in production, our findings have policy implications in that they suggest there to be at least a demand-side, market-based potential to nudge consumers who want to decrease their water footprint and follow a more sustainable diet.

Our present chapter offers valuable insights into the effectiveness of revealing information on a product's water footprint in a form of a label and on educating consumers about water constraints in the production of the food they buy (i.e., drought severity). However, there are three potential weaknesses: (1) we have captured consumers' stated preferences and not actual behaviors, (2) there is a small sample size, and (3) there is nonrepresentation of the sample for the California population. Following field studies and methodologies implemented in our own previous work (Hilger, Rafert, and Villas-Boas 2011), and given that there can be disparities between consumers' stated preferences and their actual purchases (Hensher and Bradley 1993; Batte et al. 2007), future work should extend the experimental approach into a retail-level consumer field study—using actual choices rather than survey choices to assess consumer responses and valuations for water efficiency and based on a larger and more representative sample. Furthermore, future work should repeat the survey during nondrought years, given that the WTP estimates may be different if the analysis is performed in years when water is perceived to be more plentiful.

20. Estimates obtained by using the reported costs to farmers ranging from $1,000 to $1,800 per cubic acre, given that one cubic acre corresponds to 325,851 gallons. Source: Bloomberg, "California Water Prices Soar for Farmers as Drought Grows," accessed April 28, 2017, http://www.bloomberg.com/news/articles/2014-07-24/california-water-prices-soar-for-farmers-as-drought-grows.

Appendix

Survey for CA Choices

thank you for participating in this survey.

* Required

1. **What is your gender** *

Mark only one oval.

- male
- female

2. **What is your age** *

Mark only one oval.

- 18-20
- 21-29
- 30-39
- 40-49
- 50-59
- 60 or older

3. **What is your highest level of education** *

Mark only one oval.

- Less than high school degree
- High School degree or equivalent (e.g. GED)
- Some college but no degree
- Bachelor degree
- graduate degree

4. **What is your household income** *

Mark only one oval.

- less than $25,000
- $25,000 to $49,000
- $50,000 to 75,000
- $75,000 to $100,000
- $100,000 to $125,000
- $125,000 to $150,000
- $150,000 or more

Fig. 8A.1 Survey instrument

5. **How many people live in your household?** *
Mark only one oval.

- ⬭ 1
- ⬭ 2
- ⬭ 3
- ⬭ 4
- ⬭ 5 or more

6. **What is your race** *
Mark only one oval.

- ⬭ White
- ⬭ Hispanic
- ⬭ Black or African American
- ⬭ Asian
- ⬭ American Indian
- ⬭ Other: ____________

7. **Climate change is a result of human activities and is already affecting people worldwide.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

8. **Protecting the environment should be given utmost priority, even if it causes slower economic growth and some loss of jobs.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

9. **It is the government's responsibility to impose high taxes on fossil fuels.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

Fig. 8A.1 (cont.)

10. **The U.S. government should impose stricter laws on pollution.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

11. **People should pay higher prices to address climate change.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

12. **There should be more investment using tax dollars in alternative fuels.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

13. **People should make lifestyle changes to reduce environmental damage.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

14. **It is important to purchase things that are more environmentally friendly, even at a greater cost.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

15. **The current generation has a responsibility to protect the environment for future generations, even if it leaves them less well off.** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Fig. 8A.1 (cont.)

16. **Personal food choices can affect the environmental impact of agriculture** *
Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

Choices

Which of the products would you choose for your household?

17. **Avocados**

Mark only one oval.

- ⬭ $0.98 Lb, conventional, Average Water footprint of 157 gallons per Lb
- ⬭ $2.00/Lb organic, Average Water Footprint of 157 gallons per Lb
- ⬭ $1.18/ Lb Conventional, Efficient Water Footprint, 80 gallons per Lb
- ⬭ $2.40 Lb, Organic Efficient Water Footprint , 80 gallons per Lb
- ⬭ I would not purchase any of these

Fig. 8A.1 (cont.)

18. **Almonds**

Mark only one oval.

- ◯ $5.99 Lb, conventional, Average Water footprint of 1,715 gallons per Lb
- ◯ $11.59 Lb organic, Average Water Footprint of 1,715 gallons per Lb
- ◯ $7.19 Lb Conventional, Efficient Water Footprint, 1,450 gallons per Lb
- ◯ $13.90 Lb, Organic Efficient Water Footprint , 1,450 gallons per Lb
- ◯ I would not purchase any of these

Fig. 8A.1 (cont.)

19. **Lettuce**

Mark only one oval.

- $2.17 Lb, conventional, Average Water footprint of 14.8 gallons per Lb
- $5.00 Lb organic, Average Water Footprint of 14.8 gallons per Lb
- $2.60 Lb Conventional, Efficient Water Footprint, 5.9 gallons per Lb
- $6.00 Lb, Organic Efficient Water Footprint , 5.9 gallons per Lb
- I would not purchase any of these

Fig. 8A.1 (cont.)

20. **Tomato**

Mark only one oval.

- ⬭ $1.56 Lb, conventional, Average Water footprint of 16.9 gallons per Lb
- ⬭ $1.99 Lb organic, Average Water Footprint of 16.9 gallons per Lb
- ⬭ $1.87 Lb, Conventional Efficient Water Footprint , 6.5 gallons per Lb
- ⬭ $2.39 Lb Organic, Efficient Water Footprint, 6.5 gallons per Lb
- ⬭ I would not purchase any of these

Fig. 8A.1 (cont.)

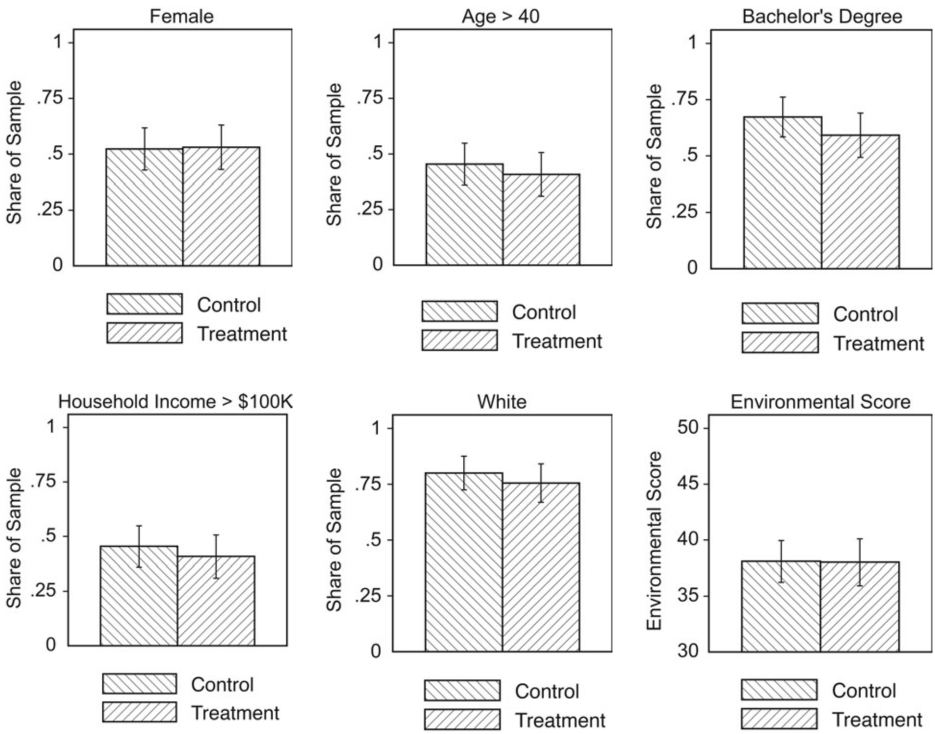

Fig. 8A.2 Average respondent characteristics for treatment and control groups

Notes: The figure displays the average demographic characteristics of respondents for the control and for the treatment groups separately. Environmental score has a minimum value of 10 if a respondent strongly disagreed with all 10 of the environmental statements and a maximum of 50 if the respondent strongly agreed with all of the same 10 statements.

Source: Survey. N = 208 observations.

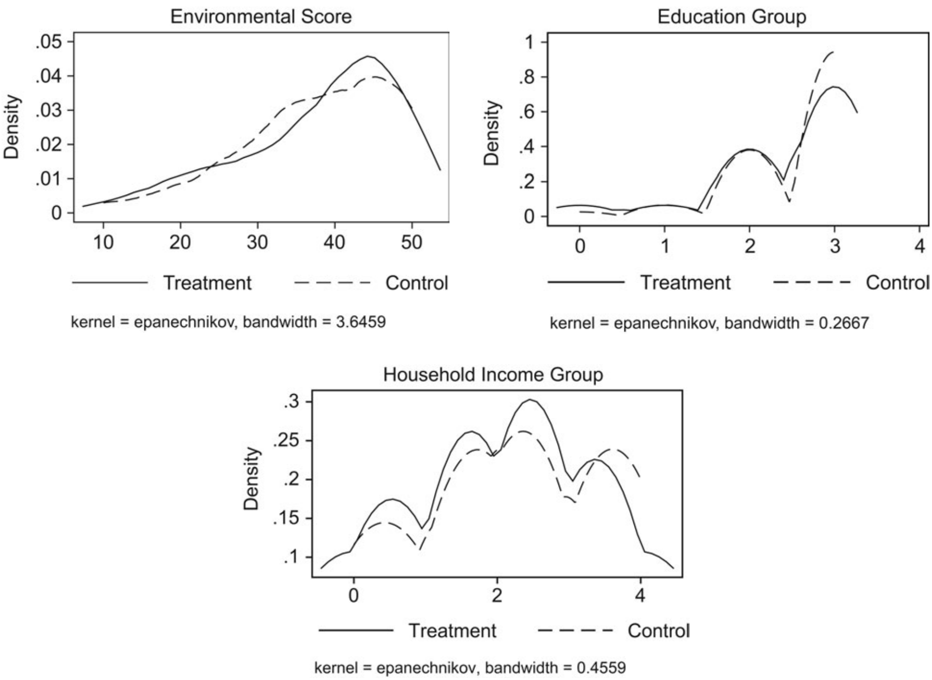

Fig. 8A.3 Kernel density estimates and test of distribution equality

Notes: The figure displays the kernel density estimates of characteristics of respondents for the control and for the treatment groups separately and tests for equality using the Kolmogorov-Smirnov test. Kolmogorov-Smirnov test for equal distribution (*p*-values in parentheses): environmental score = 0.075 (0.943), education = 0.0748 (0.936), income = 0.1183 (0.481).

Source: Survey. N = 208 observations.

References

Abidoye, B. O., H. Bulut, J. Lawrence, B. Mennecke, and A. M. Townsend. 2011. "US Consumers' Valuation of Quality Attributes in Beef Products." *Journal of Agricultural and Applied Economics* 43 (1): 1–12.
Aguilar, F., and R. P. Vlosky. 2007. "Consumer Willingness to Pay Price Premiums for Environmentally Certified Wood Products in the US." *Forest Policy and Economics* 9:1100–12.
Alfnes, F., A. Guttormensen, G. Steine, and K. Kolstad. 2006. "Consumer's Willingness to Pay for the Color of Salmon: A Choice Experiment with Real Economic Incentives." *American Journal of Agricultural Economics* 88 (4): 1050–61.
Asche, F., and J. Guillen. 2012. "The Importance of Fishing Method, Gear and Origin: The Spanish Hake Market." *Marine Policy* 36 (2): 365–69.
Batte, M., N. Hooker, T. Haab, and J. Beaverson. 2007. "Putting Their Money Where Their Mouths Are: Consumer Willingness to Pay for Multi-ingredient, Processed Organic Food Products." *Food Policy* 32 (2): 145–49.
Dimitri, C., and C. Greene. 2002. "Recent Growth Patterns in the US Organic Foods Market." *Agriculture Information Bulletin* 777. Washington, DC: US Department of Agriculture Economic Research Service.
Gao, Z., and T. Schroeder. 2009. "Effects of Label Information on Consumer Willingness-to-Pay for Food Attributes." *American Journal of Agricultural Economics* 91 (3): 795–809.
Hallstein, E., and S. B. Villas-Boas. 2013. "Can Household Consumers Save the Wild Fish? Lessons from a Sustainable Seafood Advisory." *Journal of Environmental Economics and Management* 66 (1): 52–71.
Hanak, E., J. Mount, C. Chappelle, J. Lund, J. Medellin-Azuara, P. Moyle, and N. Seavy. 2015. "What If California's Drought Continues?" Public Policy Institute of California, August. Accessed April 28, 2017. http://www.ppic.org/content/pubs/report/R_815EHR.pdf.
Hensher, D., and M. Bradley. 1993. "Using Stated Response Data to Enrich Revealed Preference Discrete Choice Models." *Marketing Letters* 4 (2): 139–52.
Hilger, J., G. Rafert, and S. Villas-Boas. 2011. "Expert Opinion and the Demand for Experience Goods: An Experimental Approach in the Retail Wine Market." *Review of Economics and Statistics* 93 (4): 1289–96.
Howitt, R., J. Medellín-Azuara, D. MacEwan, J. Lund, and D. Sumner. 2015. "Economic Analysis of the 2015 Drought for California Agriculture." UC Davis Center for Watershed Sciences.
Huber, J., and K. Train. 2001. "On the Similarity of Classical and Bayesian Estimates of Individual Mean Partworths." *Marketing Letters* 12 (3): 259–69.
Jaffry, S., H. Pickering, Y. Ghulam, D. Whitmarsh, and P. Wattage. 2004. "Consumer Choices for Quality and Sustainability Labelled Seafood Products in the UK." *Food Policy* 29 (3): 215–28.
Kiesel, K., and S. B. Villas-Boas. 2007. "Got Organic Milk? Consumer Valuations of Milk Labels after the Implementation of the USDA Organic Seal." *Journal of Agricultural and Food Industrial Organization* 5 (1): 1–38.
Lee, K. H., and C. B. Hatcher. 2001. "Willingness to Pay for Information: An Analyst's Guide." *Journal of Consumer Affairs* 35 (1): 120–39.
Macdiarmid, J. 2012. "Is a Healthy Diet an Environmentally Sustainable Diet?" *Proceedings of the Nutrition Society* 72 (1): 13–20.
Mann, M., and P. Gleick. 2015. "Climate Change and California Drought in the 21st Century." *Proceedings of the National Academy of Sciences* 112 (3): 3858–59.

McConnell, K. E., and I. E. Strand. 2000. "Hedonic Prices for Fish: Tuna Prices in Hawaii." *American Journal of Agricultural Economics* 82 (1): 133–44.
McFadden, D. 1974. "The Measurement of Urban Travel Demand." *Journal of Public Economics* 3 (4): 303–28.
McFadden, D., and K. Train. 2000. "Mixed MNL Models for Discrete Response." *Journal of Applied Econometrics* 15 (5): 447–70.
Mekonnen, M. M., and A. Y. Hoekstra. 2011. "The Green, Blue and Grey Water Footprints of Crops and Derived Crop Products." *Hydrology and Earth System Sciences* 15 (5): 1577–1600.
Renault, D. 2002. "Value of Virtual Water in Food: Principles and Virtues." Paper presented at the UNESCO-IHE Workshop on Virtual Water Trade, December 12–13, Delft, Netherlands.
Revelt, D., and K. Train. 2000. "Customer-Specific Taste Parameters and Mixed Logit: Households' Choice of Electricity Supplier." Working Paper no. E00-274, Department of Economics, University of California, Berkley.
Roheim, C. A., F. Asche, and J. I. Santos. 2011. "The Elusive Price Premium for Eco-Labelled Products: Evidence from Seafood in the UK Market." *Journal of Agricultural Economics* 62 (3): 655–68.
Roheim, C. A., L. Gardiner, and F. Asche. 2007. "Value of Brands and Other Attributes: Hedonic Analysis of Retail Frozen Fish in the UK." *Marine Resource Economics* 22 (3): 239–53.
Small, K., and H. Rosen. 1981. "Applied Welfare Economics with Discrete Choice Models." *Econometrica* 49 (1): 105–30.
Smith, B. G. 2008. "Developing Sustainable Food Supply Chains." *Philosophical Transactions of the Royal Society: Biological Sciences* 363 (1492): 849–61.
Tait, P., S. Miller, W. Abell, W. Kaye-Blake, M. Guenther, and C. Saunders. 2011. "Consumer Attitudes towards Sustainability Attributes on Food Labels." Paper presented at the 55th Annual AARES National Conference, Melbourne, Victoria.
Teisl, M., B. Roe, and R. Hicks. 2002. "Can Eco-Labels Tune a Market? Evidence from Dolphin Safe Labeling." *Journal of Environmental Economics and Management* 43 (3): 339–59.
Train, K. 2003. *Discrete Choice Methods with Simulation*. New York: Cambridge University Press.