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Revisiting Opt-Out Responses and Consequentiality in Contingent Valuation

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This paper revisits the topic of opt-out responses in contingent valuation from a fresh perspective. We first acknowledge the probabilistic nature of referendum-style contingent valuation and set up the expected utility framework. Within this framework, we show conditions under which opting out is consistent with the random utility model. Also, we test empirically whether opt-out responses are more similar to yes or no votes and examine consequences of discarding opt-out responses in terms of parameter estimates, sample means, and welfare estimates. We present empirical tests that can be used as criteria to decide what to do with opt-out responses.

Key words: consequentiality, contingent valuation, nonmarket valuation, opt-out option

Introduction

In 1993, the National Oceanic and Atmospheric Administration (NOAA) appointed a panel of prominent social scientists, led by Kenneth Arrow, to assess reliability of the contingent valuation (CV) method (Arrow et al. 1993). This "NOAA Blue Ribbon Panel" concluded that CV can produce reliable welfare estimates if properly executed. Following their conclusion, the panel issued guidelines for designing ideal CV surveys. One of the recommendations was to allow respondents to opt out of the referendum question. The panel did not provide guidance on how to implement the option, but in the literature, it is typically done by including an "I don't know" option, in addition to Yes and No, as a response to the referendum question ("Are you in favor of the proposed project?") (e.g., Wang, 1997; Haener and Adamowicz, 1998; Groothuis and Whitehead, 2002).

The panel also did not provide guidelines on what to do with such responses. In the literature, one practice is to discard such responses from welfare estimation (Wang, 1997). There are two potential issues with this practice. First, it can be costly. Studies in the literature have found that a substantial portion of the sample opts out (e.g., 25 percent (Arrow et al. 1993); 36 percent (Groothuis and Whitehead, 2002); 18 percent (Haener and Adamowicz, 1998); and 30 percent (Wang, 1997)). Second, as Wang (1997) pointed out, discarding such responses implicitly assumes that socioeconomic and other individual-specific characteristics of those who opt out are the same as the rest of the sample. If not, the study may suffer from sample selection bias. According to the survey literature, respondents who have more knowledge or experience with the topic (Converse, 1976; Durand and Lambert, 1988; Faulkenbeny and Mason, 1978; Krosnick and Milbum, 1990; Rapoport 1981; Wright and Niemi, 1983) are less likely to opt out**.** Also,

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respondents who have higher levels of education (Bishop, Oldendick, and Tuchfarber 1980; Schuman and Presser, 1981), higher cognitive skills (Colsher and Wallace, 1989 Sigelman, Winer, and Schoenrock, 1982), and who are younger, male, white, and/or wealthier (Converse, 1976; Francis and Busch, 1975; Rapoport, 1982) are less likely to opt out. Therefore, there is empirical evidence that this practice may not be ideal.

Consequently, there have been efforts in the literature to find a way to utilize such responses. Carson et al. (1998) used a split-sample approach where one version included the opt-out option and the other did not, and found that inclusion of the opt-out option did not significantly change the proportion of Yes votes, implying that respondents who opted out would have chosen No if such an option was not offered. They concluded that opt-out responses can be recoded as No responses. Groothuis and Whitehead (2002) found that if respondents are forced to make a choice between Yes and No, they will choose No in a willingness-to-pay (WTP) setting but choose Yes in willingness-to accept (WTA) setting. Balcombe and Fraser (2009) found that opt-out responses are more similar to Yes than No, but that they should not be pooled with other responses. Wang (1997) argued that respondents have a range of WTP rather than a single value and will choose to opt out if the offered bid is very close to the middle point of their WTP range because it is difficult for them to determine which alternative is optimal.

Hwang, Petrolia, and Interis (2014) empirically examined effects of consequentiality on opt-out. Consequentiality is a perception that respondents believe that their choices in the survey will affect the policy outcome and is a condition for respondents to reveal their truthful preferences (Carson and Groves, 2007). A survey question is consequential if the respondent believes her response will affect some outcome that she cares about. From such questions we can expect "useful information" (Carson and Groves, 2007, p. 183). Previous work has found that respondents who perceive a survey to be inconsequential behave differently from those who perceive it as consequential (Bulte et al. 2005; Herriges et al. 2010; Vossler and Watson 2013; Interis and Petrolia 2014).

This paper revisits the topic of opt-out responses in CV and presents a comprehensive analysis from a fresh perspective. The primary goals of this study are 1) to examine theoretically why respondents opt out; 2) to test our theoretical findings empirically; 3) to test empirically if opt-out is similar to yes or no; and 4) to examine consequences of discarding opt-out responses. For the empirical analysis, we use datasets from two different CV surveys which both focused on coastal wetlands in the Gulf of Mexico region (Louisiana and Florida); included an opt-out option in the referendum; and the option was identically labeled ("I prefer not to vote"). Following the literature (e.g., Carson et al., 1998; Chambers and Whitehead, 2003; Groothuis and Whitehead, 2002; Haener and Adamowicz, 1998; Hwang, Petrolia, and Interis, 2014), we first treat opt-out as a distinct alternative to Yes and No. Although there have been several studies that tested whether opt-out is similar to yes or no, this paper is the first to examine the question using the scale parameter that captures similarity or substitutability between alternatives. We examine consequences of discarding opt-out responses from estimation based on three criteria: beta estimates, sample means, and WTP estimates. We find that respondents with well-defined preferences (i.e., they know which option they prefer) will still opt out if they perceive the survey as inconsequential, thus inconsistent with the commonly used "don't know" interpretation.

Theory

The Probabilistic Nature of Referendum-Style CV

CV is one of several tools used by economists to estimate the value of both market and nonmarket goods (Carson, 2000). In a market good setting, although it is hypothetical, it is assumed that a choice that a respondent makes is consistent with her utility of consuming the good directly at a given cost. In a nonmarket good setting, however, a respondent's choice does not directly result in implementation of a proposed program. The program may or may not be implemented, and each respondent is given an opportunity to affect the likelihood of implementation. Therefore, utilities of a respondent *i* voting yes, U_{iyes} and no, U_{ino} may not necessarily represent utilities of "consuming" or having the program, U_{iP} and not having the program, U_{iNP}, respectively. If the program is not implemented, a respondent *i* will not obtain the quality/quantity changes proposed in the program even if they voted yes. Similarly, if the program is implemented, everyone in the area of interest will be affected including those who voted against it. Therefore, there are four possible outcomes; 1) a respondent chooses yes, and the program is implemented, 2) a respondent chooses yes, and the program is not implemented, 3) a respondent chooses no, and the program is implemented, and 4) a respondent chooses no, and the program is not implemented. Vossler, Doyon, and Rondeau (2012) recognized the probabilistic nature of referendum-style CV and adopted the expected utility framework. To adopt the expected utility framework, they developed the "policy function" that affects the probability of a policy being implemented which accounts for votes cast in the survey, policymakers' preferences, constraints, and other considerations that may enter the decision-making process. In this paper, we also adopt the expected utility model as Vossler, Doyon, and Rondeau suggest recognizing the probabilistic nature of CV but present an alternative way to model the issue by using the subjective likelihood perceived by survey respondents, given their choice. Let $\tilde{p}_{ij}$ be the subjective likelihood of program implementation as perceived by an individual *i* when they choose yes or no. The expected utility of choosing yes can be represented as

$$EU_{iyes} = \tilde{p}_{iyes} \cdot U_{iP} + (1 - \tilde{p}_{iyes}) \cdot U_{iNP} \tag{1}$$

where U_{iP} is the utility of having the program, and U_{iNP} is the utility of not having the program. The expected utility of choosing no can be represented as

$$EU_{ino} = \tilde{p}_{ino} \cdot U_{iP} + (1 - \tilde{p}_{ino}) \cdot U_{iNP}, \tag{2}$$

A respondent chooses yes if $EU_{iyes} - EU_{ino} > 0$.

$$\begin{aligned} EU_{iyes} - EU_{ino} &= \tilde{p}_{iyes} \cdot U_{iP} + \left(1 - \tilde{p}_{iyes}\right) \cdot U_{iNP} - \tilde{p}_{ino} \cdot U_{iP} - (1 - \tilde{p}_{ino}) \cdot U_{iNP} \\ &= \left(\tilde{p}_{iyes} - \tilde{p}_{ino}\right) \cdot (U_{iP} - U_{iNP}) > 0. \end{aligned} \tag{3}$$

Carson and Groves (2007) argued that

> *"[i]f a survey's results are not seen as having any influence on an agency's actions or the agent is indifferent to all possible outcomes of the agency's actions, then all possible responses by the agent will be perceived as having the same influence on the agent's welfare. In such a case, economic theory makes no predictions." (p. 183)*

For a respondent who perceives a CV study as consequential, $\left(\tilde{p}_{iyes} - \tilde{p}_{ino}\right) > 0$, and $EU_{iyes} - EU_{ino} > 0$ if $U_{iP} > U_{iNP}$. For a respondent who perceives a CV study as inconsequential, $\tilde{p}_{iyes} = \tilde{p}_{ino}$ such that they are indifferent between choosing yes and no in terms of expected utilities, regardless of U_{iP} *and* U_{iNP}. This simple framework demonstrates the consequentiality condition as $\tilde{p}_{iyes} > \tilde{p}_{ino}$. As long as $\tilde{p}_{iyes} > \tilde{p}_{ino}$, CV is consistent with the random utility model (RUM) despite its probabilistic nature (i.e., $EU_{iyes} > EU_{ino}$ if $U_{iP} > U_{iNP}$).

CV with Opt-Out

In a referendum-style CV in which opt-out is explicitly provided, a respondent has three alternatives: yes, no, and opt-out. Therefore, there are six possible outcomes; 1) a respondent chooses yes, and the program is implemented, 2) a respondent chooses yes, and the program is not implemented, 3) a respondent chooses no, and the program is implemented, 4) a respondent chooses no, and the program is not implemented, 5) a respondent chooses opt-out, and the program is implemented, and 6) a respondent chooses opt-out, and the program is not implemented.

Expected utilities of choosing yes and no can be represented as (1) and (2), respectively. The expected utility of choosing opt-out can be represented as

$$EU_{ioptout} = \tilde{p}_{ioptout} \cdot U_{iP} + (1 - \tilde{p}_{ioptout}) \cdot U_{iNP}. \tag{4}$$

A respondent chooses yes if $EU_{iyes} - EU_{ino} > 0$ *and* $EU_{iyes} - EU_{ioptout} > 0$. The result of $EU_{iyes} - EU_{ino}$ is previously shown in equation (3). Subtracting (4) from (1) yields:

$$\text{(5)}\quad EU_{iyes} - EU_{ioptout} = \tilde{p}_{iyes} \cdot U_{iP} + \left(1 - \tilde{p}_{iyes}\right) \cdot U_{iNP} - \tilde{p}_{ioptout} \cdot U_{iP} - (1 - \tilde{p}_{ioptout}) \cdot U_{iNP}$$
$$= \left(\tilde{p}_{iyes} - \tilde{p}_{ioptout}\right) \cdot (U_{iP} - U_{iNP}) > 0.$$

The first term, $(\tilde{p}_{iyes} - \tilde{p}_{ioptout}) > 0$ which implies $EU_{iyes} - EU_{ioptout} > 0$ if $U_{iP} > U_{iNP}$. Thus, a respondent chooses yes if $U_{iP} > U_{iNP}$ and is consistent with RUM.

A respondent chooses no if $EU_{ino} - EU_{iyes} > 0$ and $EU_{ino} - EU_{ioptout} > 0$.

$$\text{(6)}\quad EU_{ino} - EU_{iyes} = \tilde{p}_{ino} \cdot U_{iP} + (1 - \tilde{p}_{ino}) \cdot U_{iNP} - \tilde{p}_{iyes} \cdot U_{iP} - \left(1 - \tilde{p}_{iyes}\right) \cdot U_{iNP}$$
$$= \left(\tilde{p}_{ino} - \tilde{p}_{iyes}\right) \cdot (U_{iP} - U_{iNP}) > 0.$$

The first term, $(\tilde{p}_{ino} - \tilde{p}_{iyes}) < 0$ which implies $EU_{ino} - EU_{iyes} > 0$ if $U_{iP} < U_{iNP}$.

$$\text{(7)}\quad EU_{ino} - EU_{ioptout} = \tilde{p}_{ino} \cdot U_{iP} - (1 - \tilde{p}_{ino}) \cdot U_{iNP} - \tilde{p}_{ioptout} \cdot U_{iP} + (1 - \tilde{p}_{ioptout}) \cdot U_{iNP}$$
$$= \left(\tilde{p}_{ino} - \tilde{p}_{ioptout}\right) \cdot (U_{iP} - U_{iNP}) > 0.$$

The first term, $(\tilde{p}_{ino} - \tilde{p}_{ioptout}) < 0$ which implies $EU_{ino} - EU_{ioptout} > 0$ if $U_{iP} < U_{iNP}$. It is shown that a respondent chooses no if $U_{iP} < U_{iNP}$ and is consistent with RUM.

A respondent chooses opt-out if $EU_{ioptout} - EU_{iyes} > 0$ and $EU_{ioptout} - EU_{ino} > 0$.

$$\text{(8)}\quad EU_{ioptout} - EU_{iyes} = \tilde{p}_{ioptout} \cdot U_{iP} + (1 - \tilde{p}_{ioptout}) \cdot U_{iNP} - \tilde{p}_{iyes} \cdot U_{iP} - (1 - \tilde{p}_{iyes}) \cdot U_{iNP}$$
$$= \left(\tilde{p}_{ioptout} - \tilde{p}_{iyes}\right) \cdot (U_{iP} - U_{iNP}) > 0.$$

The first term, $(\tilde{p}_{ioptout} - \tilde{p}_{iyes}) < 0$ which implies $U_{iP} < U_{iNP}$. The expected utility is inconsistent with RUM in this case because the respondent is better off without the program and therefore should choose no.

$$\text{(9)}\quad EU_{ioptout} - EU_{ino} = \tilde{p}_{ioptout} \cdot U_{iP} + (1 - \tilde{p}_{ioptout}) \cdot U_{iNP} - \tilde{p}_{ino} \cdot U_{iP} - (1 - \tilde{p}_{ino}) \cdot U_{iNP}$$
$$= \left(\tilde{p}_{ioptout} - \tilde{p}_{ino}\right) \cdot (U_{iP} - U_{iNP}) > 0. \tag{10}$$

The first term, $(\tilde{p}_{ioptout} - \tilde{p}_{ino}) > 0$ which implies $U_{iP} > U_{iNP}$. The expected utility is inconsistent with RUM in this case also because the respondent is better off with the program and should choose yes.

There are two cases where a respondent chooses opt-out that become consistent with RUM. The first case is when a respondent is indifferent between utilities of possible outcomes, $U_{iP} = U_{iNP}$. This is well known as Arrows et al. pointed out for a reason for opt-out: "rough indifference between a yes and a no vote" (p. 34). The second case where the strict inequality between perceived probabilities assumption does not hold such that the difference between perceived probabilities is zero in equations (8) and (10) such that they are indifferent between possible outcomes in terms of expected utilities, regardless of their preferences, U_{iP} and U_{iNP}. There are two possibilities for the second case. One possibility is inconsequentiality. If a respondent perceives a CV study as inconsequential, they are indifferent between possible outcomes in terms of expected utilities regardless of their choice. Another possibility is about how a respondent perceives opt-out. If a respondent perceives that choosing opt-out would somehow have the same impact as choosing either yes (i.e., opt-out is similar to yes) or no (i.e., opt-out is similar to no) on the probability of the proposed program being implemented, the differences between perceived probabilities are zero in the two equations even though they perceive that voting yes (no) will increase (decrease) the probability of the proposed program being implemented ($\tilde{p}_{iyes} > \tilde{p}_{ino}$).

Data

LA Wetlands

Petrolia, Interis, and Hwang (2014) collected information on preferences for coastal wetland restoration in Louisiana. The survey was administered in 2011 via an online survey firm, Knowledge Networks. Knowledge Networks sampled respondents from their probability-based panel that is representative of the target population that was non-institutionalized adults aged 18 and over residing in the U.S. The survey had two versions: a binary CV and a multinomial DCE. In this analysis, we use the CV version only.[1] Out of 5,185 people sampled, 3,464 responded to one version or the other. Of the 3,464 that responded, 1,397 completed the CV version. The survey first explained what coastal wetlands and barrier islands are, why they are important, how much of them have been lost due to natural erosion, sea-level rise, sinking of land, winds, tides, currents, storms, and human developments. Then it proposed a large-scale (234,000 acres) restoration project that will improve ecosystem services provided by coastal wetlands. Three ecosystem services were included as expected benefits of the program: wildlife habitat, storm surge protection, and improved commercial fish harvest. Cost was randomized from a range of {$25, 90, 155, 285, 545, 925, 1,305, 2,065, 2,825}. Respondents were asked to evaluate the proposed project at a given cost and to cast their vote. To ensure the incentive compatibility for those who perceive the survey as consequential, each respondent answered only one choice task (i.e., single-bound; Carson and Groves, 2007). Out of 1,358 observations used in the analysis, 608 chose Yes (45 percent), 400 chose No (29 percent), and 350 chose opt-out (26 percent).

Perceived consequentiality was measured based on two survey questions:

When voting, how important did you think <u>your vote</u> would be in determining which option received the most votes?
a) Very important
b) Somewhat important
c) Not important
d) I didn't really think about it.

How likely do you think it is that the results of <u>this survey</u> will shape the direction of future policy in the Lower Barataria-Terrebonne Estuary?
a) Very likely
b) Somewhat likely
c) Unlikely
d) I don't know.

[1] See Petrolia, Interis, and Hwang (2014) for more details on both the binary and the multinomial choice versions of the survey.

The first question elicited respondent perceptions about the importance of their vote, whereas the second question elicited respondent perceptions about the likelihood that outcome of the survey will actually affect policy. If one believes that their vote is important in determining the outcome of the survey but does not believe that the outcome of the survey will be used in the policymaking process, it is inconsequential. Similarly, if one believes that the outcome of the survey will be used in the policy process but does not believe that their vote is important in determining the outcome of the survey, it is inconsequential. Therefore, both vote consequentiality and survey consequentiality conditions should be satisfied for consequentiality. Empirical effects of consequentiality on opt-out were previously examined in Hwang, Petrolia, and Interis (2014), but they use only the second question as the measure of perceived consequentiality. In this paper, respondents who responded "a" or "b" to both questions are categorized as consequential. The dataset also included other demographic information such as familiarity with the topic ("familiar" = 1 if at least somewhat familiar with the wetland and barrier island loss issue in coastal Louisiana; =0 otherwise), income, age, ethnicity ("white" =1 if white; =0 otherwise), education level ("bachelor's degree" =1 if has bachelor's degree or higher, =0 otherwise), gender ("male" =1 if male, =0 otherwise), marital status ("married" =1 if married, =0 otherwise), and political ideology (from 1 = extremely liberal to 7 = extremely conservative).

FL Wetlands

Hwang (2024) administered an online survey in which many of the survey questions were adapted from Petrolia, Interis, and Hwang (2014). The survey was administered via Qualtrics to collect information about Floridians' preferences for restoring wetlands in Tampa Bay. The target population was non-institutionalized adults (18 and over) who reside in the state of Florida. The survey was administered from July to September 2020. A total of 1,243 responses were collected that are representative of the population demographics in terms of age, gender, race, education, and income. After providing detailed information about wetlands and ecosystem services provided by them such as wildlife habitats, fisheries support, storm surge protection, and improved water quality, the survey described how much of wetlands have been lost in the Tampa Bay area over the years. A hypothetical restoration project was proposed which would restore wetlands in the area from 20,604 acres back to approximately 35,000 acres. In the referendum question, the cost was randomized from a range of {$50, $300, $650, $950, $1,200} and described as a one-time fee that would be added to 2021 federal income tax return. A total of 7,483 who were on the Qualtrics panel were invited to take the survey, 4,146 of them responded to the survey, and 1,243 completed responses were provided by Qualtrics after screening for demographic quotas and quality control (speed-takers, bots, etc.). Of the 1,243 respondents, 798 (64 percent) voted Yes, 259 (21 percent) voted No, and 186 (15 percent) opted out in the referendum.

Survey questions to elicit perceived consequentiality were almost identical to that of the previous survey. One question asked how important their vote would be in determining the outcome of the survey, and the other question asked how likely it was that the outcome of the survey would be used in the decision-making process. Unlike how the questions in the previous survey measured the perceptions with discrete Likert scales, the questions in this survey measured the perceptions on a scale from 0 (not important/unlikely) to 10 (very important/very likely). The consequentiality variable was constructed by aggregating responses in the two questions such that it ranges from 0 to 20. Finally, other demographic variables used in the analysis included income, age, ethnicity ("white" =1 if white; =0 otherwise), education level ("bachelor's degree" =1 if has bachelor's degree or higher, =0 otherwise), gender ("male" =1 if male, =0 otherwise), and political ideology (from 0 = extremely liberal to 10 = extremely conservative).

Econometric Methods

The probability of a respondent i choosing an alternative j can be represented as

$$(11) \qquad Prob(Y_i = j|\boldsymbol{x}_i) = \frac{exp\left(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\right)}{\sum_{j=0}^{J} exp(\boldsymbol{x}'_i\boldsymbol{\beta}_j)}, \text{ where } j = 0, 1, \dots, J$$

where $\mathbf{x}'_{\mathrm{i}}$ is a vector of individual-specific characteristics including cost that is exogenously assigned to respondents, $\boldsymbol{\beta}_{\mathrm{j}}$ is a vector of beta estimates (Greene, 2012). The multinomial logit model is estimated treating opt-out as an alternative along with yes and no.

Consequentiality and Opt-Out

Our hypothesis is that inconsequential respondents are more likely to choose opt-out. One thing to note is that parameter estimates resulted from the multinomial logit model are relative to the base alternative, no. This results in two separate sub-hypotheses to test effects of consequentiality on opt-out. $H_{1optout}\colon \beta_{consequential,optout} < 0$ indicates that consequential respondents are less likely to choose opt-out than no, or inconsequential respondents are more likely to choose opt-out than no. $H_{1yes}\colon \beta_{consequential,yes} > \beta_{consequential,optout}$ indicates that consequential respondents are more likely to choose yes than opt-out, or inconsequential respondents are more likely to choose opt-out than yes.

Is Opt-Out Similar to Yes or No?

We examine if opt-out is similar to yes or no based on two criteria: beta estimates and the scale parameter. We first test whether beta estimates between opt-out and yes, and opt-out and no are equal ($H_{2Y}\colon \boldsymbol{\beta}_{optout} = \boldsymbol{\beta}_{yes}$; $H_{2N}\colon \boldsymbol{\beta}_{optout} = \boldsymbol{\beta}_{no}$). A rejection of a hypothesis implies that opt-out should not be pooled with the corresponding alternative. The hypotheses can be tested using the Wald test.

Next, we test whether opt-out is similar to yes or no by estimating the scale parameter that measures similarity or substitutability between alternatives. The multinomial logit model above assumes that error terms of alternatives are identically and independently distributed (IID). Due to the IID assumption, the independence of irrelevant alternatives (IIA) property arises. The ratio of choice probabilities does not change with absence or presence of any other alternative in the set of alternatives (Greene, 2012). The nested logit model relaxes this property by nesting similar alternatives and allowing the variance to vary across nests. The probability of a respondent *i* choosing an alternative j within a branch B_k is

$$(12) \qquad P_{ijk} = \frac{exp\,\{(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j)/\lambda_k\}\left[\sum_{j\in B_k} exp\,\{(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j)/\lambda_k\}\right]^{\lambda_k-1}}{\sum_{l=1}^{K}\left[\sum_{j\in B_l} exp\,\{(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j)/\lambda_l\}\right]^{\lambda_l}},$$

where λ_k is a scale parameter for a branch k. The scale parameter must lie within the 0-1 range. $\lambda_k = 0$ indicates the perfect correlation between alternatives within the nest. $\lambda_k = 1$ indicates no correlation between alternatives among the nest, and the model simplifies to the multinomial logit model (Train, 2002). Further, $0 < \lambda_k < 1$ indicates that substitution between alternatives is greater than substitution between nests. As discussed earlier, the nested logit or the scale parameter is typically estimated to relax the IIA property. For example, Petrolia, Interis, and Hwang (2016) relaxed the IIA property by nesting proposed program alternatives (against no) using a discrete choice experiment (DCE) data. In this paper, however, we adopt the nested logit model to test whether or not opt-out is similar to yes or no. Two sets of nested logit regression are estimated. Table 1 describes the nest structure for two models. *Nest-Yes* hypothesizes that opt-out

Table 1. Grouping of alternatives for the nested logit model.

	Branches	
Model	*Yes*	*No*
Nest-Yes	Yes	No
(Opt-out grouped with yes)	Opt-out	
Nest-No	Yes	No
(Opt-out grouped with no)		Opt-out

is similar to yes (H_{3Y}: $0 < \lambda_{yes} < 1$) and, and *Nest-No* hypothesizes that opt-out is similar to no (H_{3N}: $0 < \lambda_{no} < 1$). The scale parameter for the degenerate nest that has only one alternative (λ_{NA} for *Nest-Yes* and λ_A in *Nest-No*) is constrained to 1.

Consequences of Discarding Opt-Out

We examine consequences of discarding opt-out based on three criteria: beta estimates, sample means, and WTP. First, we test if beta estimates between two samples are equal (H_4: $\widehat{\boldsymbol{\beta}}_2 = \widehat{\boldsymbol{\beta}}_3$). Hausman and McFadden (1984) proposed a test (a.k.a. Hausman test for IIA) that compares estimates between a full model and a model that omits an alternative. The test statistic can be constructed as

$$\chi_k^2 = \left(\widehat{\boldsymbol{\beta}}_{\mathbf{2}} - \widehat{\boldsymbol{\beta}}_{\mathbf{3}}\right)' [var(\widehat{\boldsymbol{\beta}}_{\mathbf{2}} - \widehat{\boldsymbol{\beta}}_{\mathbf{3}})]^{-1} \left(\widehat{\boldsymbol{\beta}}_{\mathbf{2}} - \widehat{\boldsymbol{\beta}}_{\mathbf{3}}\right), \tag{13}$$

where k represents the number of parameters. However, the test statistic may be undefined because the variance-covariance matrix is guaranteed to be positive definite only asymptotically, and negative values along the diagonal elements are possible (StataCorp, 2019). Weesie (1999) proposed an alternative specification that overcomes the limitation of the Hausman test. The Hausman test estimates $var(\widehat{\boldsymbol{\beta}}_{\mathbf{2}} - \widehat{\boldsymbol{\beta}}_{\mathbf{3}})$ by $var(\widehat{\boldsymbol{\beta}}_{\mathbf{2}}) - var(\widehat{\boldsymbol{\beta}}_{\mathbf{3}})$, whereas the alternative test estimates is by $var\left(\widehat{\boldsymbol{\beta}}_{\mathbf{2}}\right) - 2 \cdot cov\left(\widehat{\boldsymbol{\beta}}_{\mathbf{2}}, \widehat{\boldsymbol{\beta}}_{\mathbf{3}}\right) + var(\widehat{\boldsymbol{\beta}}_{\mathbf{3}})$ such that the test statistic is always well defined (StataCorp, 2019). We use the "Hausman-type" test using a Stata command "suest" (StataCorp, 2019).

Second, we test if sample means between two samples are equal (H_5: $\bar{\boldsymbol{z}}_2 = \bar{\boldsymbol{z}}_3$). If respondents who chose opt-out are systematically different from the rest *and* a substantial proportion of respondents chose opt-out, sample means could be different between the samples. This hypothesis can be tested using the Hotelling's T-squared generalized means test. Following StataCorp (2019), the test statistic is

$$T^2 = (\bar{\boldsymbol{z}}_2 - \bar{\boldsymbol{z}}_3)\widehat{\boldsymbol{v}}^{-1}(\bar{\boldsymbol{z}}_2 - \bar{\boldsymbol{z}}_3)', \tag{14}$$

where $\widehat{\boldsymbol{v}}^{-1}$ is the pooled variance-covariance matrix. The test statistic is then used to formulate the *F*-test statistic:

$$F_{k,n_2+n_3-1} = \frac{(n_2+n_3-k-1)}{(n_2+n_3-2)k} \cdot T^2, \tag{15}$$

where n_2 and n_3 represent the number of observations for *Sample-2* and *Sample-3*. Table 2 presents summary statistics for *Sample-2* and *Sample-3*.

The ultimate goal of a CV is to obtain a WTP estimate from elicited preferences, and our interest here is to examine consequences of discarding opt-outs. We lastly compare WTPs between two samples. *Sample-2* includes responses for two alternatives (yes and no; opt-out discarded), whereas *Sample-3* includes responses for three alternatives (yes, no, and opt-out). The expected WTP from a CV is calculated as

Table 2. Summary Statistics.

	LA Wetlands		*FL Wetlands*	
	Excluding Opt-outs N=1,008	Including Opt-outs N=1,358	Excluding Opt-outs N=1,057	Including Opt-outs N=1,243
Variable	Mean (Std. Dev.)			
Consequential	0.40	0.34	13.61 (4.71)	13.19 (4.81)
Familiar	0.36	0.32	-	-
Income	75,910.22 (51,509.60)	70,542.16 (50,167.02)	65,804.16 (52,426.14)	62,860.02 (51,487.59)
Age	48.40 (16.87)	48.84 (16.79)	44.55 (16.57)	44.97 (16.79)
White	0.78	0.75	0.66	0.67
Bachelor's degree	0.38	0.33	0.31	0.28
Male	0.50	0.49	0.54	0.52
Married	0.57	0.56	-	-
Conservative	4.18 (1.55)	4.14 (1.62)	5.56 (2.83)	5.54 (2.82)

(16) $$E(WTP_s) = -\frac{\widehat{\boldsymbol{\beta}}_s{}^{*}}{\hat{\beta}_{cost,s}} \cdot \bar{\boldsymbol{z}}_s,$$

where s={2, 3; 2 and 3 refers to *Sample-2* and *Sample-3*, respectively}, $\hat{\beta}_{cost,s}$ is an estimated parameter for cost for sample s, $\widehat{\boldsymbol{\beta}}_s{}^{*}$ is a vector of parameter estimates for sample s except the estimated parameter for cost, and $\bar{\boldsymbol{z}}_s$ is a vector of sample characteristics included in regression evaluated at mean (Haab and McConnell, 2003). Confidence intervals are calculated using the Delta method (Greene, 2012). We test if the two samples yield the same WTP estimates; H_6: $E(WTP_2) = E(WTP_3)$ based on the two-sample z-test using the asymptotic variance of WTP for two samples resulted from the Delta method.

Interactions between Consequentiality and Other Individual-Specific Variables

Effects of consequentiality on respondent choices may be dependent upon other factors. For example, the effect of consequentiality for those who are familiar with the topic of interest may be different from those who are not familiar with the topic. We further investigate effects of consequentiality by interacting it with other individual-specific variables.

Results

Tables 3 and 4 present regression results for *LA Wetlands* and *FL Wetlands*, respectively. In each of the tables, the first set of results presents the multinomial logit model with all three alternatives: yes, no, and opt-out. The second set of results presents the binary logit model with two alternatives: yes and no. The last set of results on the bottom of the tables presents key results from two nested logit models, *Nest-Yes* which groups opt-out with yes and *Nest-No* which groups opt-out with no.

Table 3. LA Wetlands Regression Results

	Including Opt-outs (N=1,358) Multinomial Logit						Excluding Opt-outs (N=1,008) Logit		
	Yes			Opt-out					
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Cost	-0.001	***	0.000	0.000		0.000	-0.001	***	0.000
Consequential	1.223	***	0.153	-0.495	**	0.197	1.253	***	0.155
Familiar	0.210		0.150	-0.487	***	0.182	0.251		0.154
Income	0.000		0.000	-6.10e-06	***	0.000	0.000		0.000
Age	0.010	**	0.004	0.017	***	0.005	0.010	**	0.005
White	-0.277		0.178	-0.919	***	0.186	-0.242		0.184
Bachelor's degree	-0.096		0.159	-0.594	***	0.190	-0.118		0.163
Male	-0.120		0.141	-0.266	*	0.156	-0.085		0.146
Married	-0.567	***	0.152	-0.222		0.170	-0.569	***	0.157
Conservative	-0.284	***	0.047	-0.217	***	0.051	-0.322	***	0.051
Constant	1.567	***	0.322	1.717	***	0.350	1.663	***	0.334
Log-likelihood	-1,255.965						-577.404		
	Nested Logit								
	Nest-Yes			*Nest-No*					
	Coef.		S.E.	Coef.		S.E.			
Scale parameter	2.281		0.639	1.993		0.793			
Log-likelihood	-1,253.224			-1,254.988					

Note: *, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

Table 4. FL Wetlands Regression Results

	Including Opt-outs (N=1,243) Multinomial Logit						Excluding Opt-outs (N=1,057) Logit		
	Yes			Opt-out					
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Cost	-0.0004	**	0.0002	-0.0003		0.0002	-0.0004	**	0.0002
Consequential	0.172	***	0.017	-0.002		0.021	0.173	***	0.018
Income	2.65e-06		1.75e-06	-4.49e-06	*	2.55e-06	3.04e-06	*	0.000
Age	-0.020	***	0.005	-0.003		0.007	-0.021	***	0.005
White	-0.095		0.199	-0.279		0.254	-0.122		0.200
Bachelor's degree	0.001		0.201	-0.534	*	0.282	-0.050		0.202
Male	0.024		0.165	-0.227		0.208	0.006		0.166
Conservative	-0.087	***	0.029	-0.038		0.038	-0.099	***	0.030
Constant	0.515		0.364	0.887	**	0.448	0.634	*	0.371
Log-likelihood	-989.235						-507.744		
	Nested Logit								
	Nest-Yes			*Nest-No*					
	Coef.		S.E.	Coef.		S.E.			
Scale parameter	0.859		0.685	2.043		3.382			
Log-likelihood	-989.214			-989.181					

Note: *, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

Consequentiality and opt-out

As discussed earlier, we have two sub-hypotheses to test the relationship between consequentiality and opt-out. *LA Wetlands* results show that the estimated parameter for *Consequential* for opt-out is negative and statistically significant, indicating that consequential respondents are less likely to choose opt-out than No, or said differently, inconsequential respondents are more likely to choose opt-out than no. Therefore, we confirm $H_{1optout}$. The estimated parameter for *Consequential* for yes is positive and statistically significant, indicating that consequential respondents are more likely to choose yes than no. Therefore, we confirm H_{1yes}.

Results from *FL Wetlands* show that the estimated parameter for *Consequential* for yes is positive and statistically significant indicating that consequential respondents are more likely to choose yes than no. Therefore, we confirm H_{1yes}. However, the estimated parameter for *Consequential* for opt-out is not statistically significant, indicating that inconsequential respondents are more likely to choose yes, but there is no difference between them choosing no and opt-out.

Is opt-out Similar to Yes or No?

Let us first focus on whether opt-out is similar to yes or no in terms of parameter estimates. For H_{2Y}: $\boldsymbol{\beta}_{optout} = \boldsymbol{\beta}_{yes}$, the Wald statistic, χ^2_{10} is 109.26 for *LA Wetlands*, indicating that we reject H_{2Y}. For H_{2N}: $\boldsymbol{\beta}_{optout} = \boldsymbol{\beta}_{no}$, the Wald statistic is 190.38, indicating that we also reject H_{2N}. For *FL Wetlands*, the Wald statistic, χ^2_8 for H_{2Y} and H_{2N} is 115.45 and 19.44, respectively. Therefore, we reject both at the 5 percent confidence level. Therefore, parameter estimates for opt-out are similar to neither yes nor no for both samples. However, one may be concerned with a potential multiple comparison problem that is the probability of a false rejection increases as the number of hypotheses increases (Gelman, Hill, and Yajima, 2012). *LA Wetlands* includes 10 parameters, and *FL Wetlands* includes 8 parameters in the model which means there are 10 and 8 sub-hypotheses being tested for the equality test as a vector, respectively. Bonferroni correction suggests that the confidence level (a) for a multiple comparison test should be adjusted as $\frac{a}{m}$, where m is the number of sub-hypotheses (Gelman, Hill, and Yajima, 2012). The confidence level with the correction becomes $\frac{0.05}{10} = 0.005$ for *LA Wetlands* and $\frac{0.05}{8} = 0.00625$ for *FL Wetlands*. Given the p-value for both H_{2Y} and H_{2N} is 0.0000 for *LA Wetlands*, we still reject the nulls with the correction. As for *FL Wetlands*, the p-value for H_{2Y} and H_{2N} is 0.0000 and 0.0127, respectively. Therefore, with the correction, we reject H_{2Y} and fail to reject H_{2N}. It should be noted that the correction addresses the potential false rejection problem (i.e., type-1 error) but at the expense of introducing a potential type-2 error (Gelman, Hill, and Yajima, 2012). Readers should use their discretion interpreting these results.

Next, we proceed to the scale parameter. *Nest-Yes* hypothesizes that opt-out is similar to yes and groups them together. The scale parameter, λ_A captures similarity or substitutability between opt-out and yes. For *LA Wetlands*, the likelihood ratio test statistic χ^2_1 = 5.48 indicates that the scale parameter is statistically different from 1, and we reject $\lambda_A = 1$. However, the scale parameter is 2.28 and is outside the range of 0-1. The scale parameter greater than 1 implies that substitution between nests is greater than substitution between alternatives (Train, McFadden, and Ben-Akiva, 1987) and is inconsistent with the RUM (Hensher, Rose, and Greene, 2005; StataCorp, 2019). For *FL Wetlands*, the scale parameter is within the correct range but is not statistically significant ($\chi^2_1 = 0.84$).

Nest-No hypothesizes that opt-out is similar to no. For *LA Wetlands,* the scale parameter, λ_{NA} is outside the range, and the likelihood ratio test statistic χ^2_1 = 1.95 indicates that we fail to reject $\lambda_{NA} = 1$. For FL Wetlands, the scale parameter is also outside the range and is not significant

Table 5. Willingness to Pay Estimates.

Data	Including Opt-outs	Excluding Opt-outs
LA Wetlands	\$1,370.07 (\$1,069.56, \$1,670.58)	\$1,424.31 (\$1,128.36, \$1,720.26)
FL Wetlands	\$3,530.37 (\$1,075.27, \$5,985.47)	\$3,594.75 (\$1,174.48, \$6,015.03)

Note: 95% confidence intervals are in parentheses.

($\chi^2_1 = 0.74$). These results indicate that either opt-out is similar to neither yes nor no, or the nested model is not appropriate to test the similarity between the alternatives. Therefore, our overall findings indicate that opt-out is different from yes and no for both samples but only in terms of parameter estimates.

Consequences of Discarding opt-out

The Hausman-type test is used to test H_4: $\widehat{\boldsymbol{\beta}}_2 = \widehat{\boldsymbol{\beta}}_3$. It tests whether parameter estimates for alternative yes from the multinomial logit model for *Sample-3* and parameter estimates from the binary logit model for *Sample-2* are equal. For *LA Wetlands*, χ^2_{11} = 11.58 indicates that we fail to reject H_4. For *FL Wetlands*, χ^2_9 = 6.62 indicates that we fail to reject H_4. Therefore, we conclude that discarding opt-out does not affect parameter estimates.

The Hotelling's T-squared generalized means test is used to test H_5: $\bar{\boldsymbol{z}}_2 = \bar{\boldsymbol{z}}_3$. For *LA Wetlands*, Hotelling's T-squared test statistic is 25.95. The statistic is then used to formulate the $F_{9,2356}$ statistic that is 2.87, which indicates that we reject H_5. We conclude that sample means for *Sample-2* and *Sample-3* are statistically different for *LA Wetlands*. For *FL Wetlands*, the Hotelling's T-squared test statistic is 6.54, and $F_{7,2292}$ is 0.93. Therefore, we fail to reject H_5 for *FL Wetlands*.

Table 5 presents WTP estimates from the multinomial logit model for *Sample-3* and the logit model for *Sample-2*. For *LA Wetlands*, the estimated WTP for a proposed coastal wetland restoration project in Louisiana is \$1,370.07 for *Sample-3* and \$1,424.31 for *Sample-2*. The two-sample z-test statistic is 0.25 which indicates that we fail to reject H_6: $E(WTP_2) = E(WTP_3)$. For *FL Wetlands*, there was virtually no difference in the estimated WTP (\$3,530.37 for *Sample-3* and \$3,594.75 for *Sample-2*). Therefore, we find that discarding opt-out responses does not affect WTP estimates for the two samples.

Interactions between Consequentiality and Other Individual-Specific Variables

Tables 6 presents regression results where consequentiality is interacted with other individual-specific variables. Interpretation of parameter estimates changes with the interaction terms. Parameters for the interaction terms represent effects of the corresponding variables when respondents are consequential. Parameters for the "main effects" that are not interacted with consequentiality, on the other hand, represent effects of the corresponding variables when respondents are inconsequential. The estimated parameter for the interaction term between consequentiality and familiarity with the topic for *LA Wetlands* is positive and statistically significant for both yes and opt-out, indicating that those who are consequential and familiar are more likely to choose yes and opt-out than no, or alternatively, those who are consequential but unfamiliar with the topic are less likely to choose yes and opt-out than no. The estimated parameter for familiarity is statistically significant only for opt-out and is negative, indicating that those who are inconsequential but familiar with the topic are less likely to choose opt-out than no, or alternatively, those who are inconsequential and unfamiliar with the topic are more likely to

Table 6. Multinomial Logit Regression Results where Consequentiality Is Interacted with Other Individual-Specific Variables.

	LA Wetlands						*FL Wetlands*					
	Yes			Opt-out			Yes			Opt-out		
	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Cost	-0.001	***	0.000	0.000		0.000	-0.0005	**	0.000	0.000		0.000
Consequential	1.230	*	0.700	-0.515		0.861	0.275	***	0.069	0.125		0.082
Familiar	0.026		0.189	-0.680	***	0.212						
Income	0.000		0.000	0.000	***	0.000	0.000		0.000	0.000		0.000
Age	0.006		0.005	0.016	***	0.005	-0.026	*	0.016	-0.005		0.017
White	-0.190		0.221	-0.893	***	0.212	1.007	*	0.581	0.416		0.639
Bachelor's degree	-0.104		0.195	-0.622	***	0.216	-0.518		0.594	-0.669		0.708
Male	-0.285	*	0.173	-0.302	*	0.176	1.139	**	0.482	0.955	*	0.530
Married	-0.581	***	0.185	-0.088		0.191						
Conservative	-0.230	***	0.055	-0.173	***	0.056	-0.027		0.081	0.072		0.092
Consequential*Familiar	0.641	**	0.327	0.837	**	0.426						
Consequential*Income	0.000		0.000	0.000	**	0.000	0.000		0.000	0.000		0.000
Consequential*Age	0.014		0.010	0.010		0.012	0.000		0.001	0.000		0.001
Consequential*White	-0.244		0.390	-0.123		0.460	-0.092	**	0.045	-0.064		0.053
Consequential*Bachelor's degree	0.202		0.350	0.341		0.468	0.045		0.046	0.014		0.060
Consequential*Male	0.445		0.310	0.005		0.399	-0.097	**	0.038	-0.109	**	0.045
Consequential*Married	-0.021		0.337	-0.649		0.427						
Consequential*Conservative	-0.218	**	0.111	-0.224		0.138	-0.005		0.006	-0.010		0.007
Constant	1.568	***	0.380	1.673	***	0.387	-0.649		0.843	-0.472		0.937
Log-likelihood	-1243.585						-981.725					

Note: *, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

choose opt-out than no. The estimated parameter for consequentiality no longer contains meaningful information because it is interacted with multiple variables (technically, it is the effect of consequentiality when all the other variables are zero).

Overall, the vast majority of the estimated parameters for the interaction terms are not statistically significant, and the estimated parameters for the main effects are relatively more statistically significant. For example, the estimated parameter for bachelor's degree is negative and statistically significant for opt-out for *LA Wetlands*, indicating that those who are inconsequential and have a bachelor's degree are less likely to choose opt-out, or alternatively, those who are inconsequential and do not have a bachelor's degree are more likely to choose opt-out.[1] However, the estimated parameter for the interaction term between consequentiality and bachelor's degree is not statistically significant. These findings indicate that the individual-specific factors tend to not affect respondent choices in the referendum when they are consequential. However, when respondents are inconsequential, individual-specific factors tend to affect their choices.

Discussion

To our knowledge, this paper is the first in the literature to present a theoretical framework that explains opt-out behavior in a CV setting using expected utility. Within this framework, we found that the expected utility framework for a referendum-style CV is consistent with the RUM as long as a respondent perceives CV as consequential. We found two cases where a respondent chooses opt-out that are consistent with RUM. The first case is when a respondent is indifferent between the possible outcomes presented in the referendum. This is consistent with Arrows et al.'s a reason for choosing opt-out: indifference between Yes and No. The second case is when a respondent is indifferent between expected utilities of possible outcomes regardless of their preferences (i.e., U_{iP} and U_{iNP}). Two possibilities for the second case were discussed: inconsequentiality and opt-out being perceived as equivalent to either yes or no. Wang (1997) noted that the rationale for Arrows et al.'s recommendation is that without opt-out, "there might be a comparable percentage of respondents who give yes / no responses but whose answers do not reflect meaningful preferences on issues of concern (p. 219)." Carson and Groves (2007) also noted that economic predictions cannot be made for a respondent who perceives a CV study as inconsequential. Given that we found that inconsequential respondents are more likely to choose opt-out, we conclude that the role of including opt-out is to filter out "bad" Yes and No responses. Not all inconsequential respondents should choose opt-out, but without the option, they are forced to choose between yes and no. Opt-out filters out at least some of the inconsequential responses and improves the quality of yes and no responses in data. Moreover, even though $\tilde{p}_{ipnv} = \tilde{p}_{iyes}$ and $\tilde{p}_{ipnv} = \tilde{p}_{ino}$ may be theoretically possible even for a consequential respondent if they somehow perceive that choosing opt-out would have the same impact as choosing yes and no, our empirical findings indicate that opt-out is similar to neither yes nor no. Therefore, we conclude that between inconsequentiality and opt-out being similar to yes or no, it is inconsequentiality that is likely to cause expected utilities to be the same regardless of their preferences.

Another contribution of this paper is the interpretation of the opt-out option. Although opt-out is an option that allows respondents to choose not to answer as Arrow et al. recommended, it is commonly interpreted by researchers as an option to show preference uncertainty such as "don't know" (e.g., Wang, 1997; Haener and Adamowicz, 1998; Groothuis and Whitehead, 2002). Our finding, however, indicates that the option should not necessarily be interpreted as preference uncertainty. An opt-out response can come from a respondent with well-defined preferences but who perceives a CV survey as inconsequential. Although our results indicated that opt-out is similar to neither Yes nor No in terms of parameter estimates, we find that discarding opt-out

[1] $\beta_1 Bachelor + \beta_2 Consequential \cdot Bachelor$ is equivalent to $-\beta_1 NoBachelor - \beta_2 Consequential \cdot NoBachelor$.

responses does not affect WTP estimates. Practitioners should use caution when wording the option and interpreting responses. Also, we want to reiterate Hwang, Petrolia, and Interis (2014) by arguing that more effort needs to be made to ensure that respondents perceive CV surveys as consequential to minimize incidents where those with well-defined preferences choosing the opt-out option.

In this paper, we present empirical tests and criteria that can be applied to other CV studies. Depending on data, test results can be different from what is presented in this paper. It is up to practitioners to decide what to do with opt-out responses. For example, if the test results indicate that opt-out is similar to Yes, they may be used as a justification for recoding opt-out as Yes. We also find that individual-specific factors tend to affect respondent choices only when they are inconsequential. Typically, individual-specific or demographic variables are included in the empirical model to control for factors that are not part of the experimental design but somehow affect respondent choices. Our finding may suggest that consequentiality somehow reduces effects of factors that are not part of the CV design and ensures that observed choices are influenced by what the researcher intended. More research is needed to understand how consequentiality achieves this, and if this finding can be replicated in other CV studies and generalized.

It is important to acknowledge caveats of our analysis. First, our analysis is subject to the typical issues stated preference methods are subject to such as hypothetical bias. No actual payments were made as a result of their choice in the referendum. Respondents' decision to choose opt-out could have been different if actual payments were to be made. Second, data used in our analysis were administered via online survey companies which recruit and maintain their survey panels. Only those who were on their panel were invited to take the surveys. Furthermore, 5,185 people were invited to take either the binary CV or multinomial DCE version of the survey, and 3,464 responded to one version or the other. It is unknown how many of the 5,185 were invited to take the CV version specifically, and therefore, the exact survey response rate specific to our analysis is not available. For *FL Wetlands*, 7,483 people were invited, and 4,146 responded. However, our analysis utilized 1,243 observations provided by Qualtrics after screening for demographic quotas. We acknowledge potential sample selection bias associated with the data collection, and the proportion of those who choose opt-out could be subject to the potential sample selection bias.

In closing, it has been over 30 years since Arrow et al. (1993) recommended that researchers include an opt-out option in CV. It seems that the option is either less frequently used or how it was used and treated is not explicitly addressed in the literature anymore. However, as CV has evolved since Arrow et al., and new theories such as consequentiality have emerged, this study finds a new reason to use opt-out that was not identified at the time of Arrows et al. Given our finding, we want to remind researchers to use the option as recommended by Arrows et al. and use it correctly. Furthermore, the nested logit model is used almost exclusively for addressing the IIA property in the literature. We presented an interesting application of the model in testing whether opt-out is similar to Yes or No. We hope to see more research utilizing the model in analyzing opt-out responses.

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References

Aadland, D. and A.J. Caplan. 2003. "Willingness to pay for curbside recycling with detection and mitigation of hypothetical bias." *American Journal of Agricultural Economics* 85(2): 492–502.

Alberini, A., K. Boyle, and M. Welsh. 2003. "Analysis of Contingent Valuation Data with Multiple Bids and Response Options Allowing Respondents to Express Uncertainty." *Journal of Environmental Economics and Management* 45:40-62.

Arrow, K., R. Solow, P. Portney, E. Leamer, R. Radner, and H. Schumar. 1993. "Report of NOAA Panel on Contingent Valuation." *Federal Register* 58:4601 – 4614.

Balcombe, K. and Fraser, I. 2009. "Dichotomous-Choice Contingent Valuation with 'Dont Know' Responses and Misreporting." *Journal of Applied Econometrics* 24:1137-1152.

Bishop, G.F., R.W. Oldendick, and A.J. Tuchfarber. 1980. "Experiments in Filtering PoliticalOpinions." Political Behavior 2(4): 339–369.

Brown, T.C., I. Ajzen, and D. Hrubes. 2003. "Further tests of entreaties to avoid hypothetical bias in referendum contingent valuation." *Journal of Environmental Economics and Management* 46(2): 353–361.

Bulte, E., S. Gerking, J.A. List, and A. de Zeeuw. 2005. "The Effect of Varying the Causes of Environmental Problems on Stated WTP Values: Evidence from a Field Study." *Journal of Environmental Economics and Management* 49:330–342.

Champ, P.A. and R.C. Bishop. 2001. "Donation payment mechanisms and contingent valuation: An empirical study of hypothetical bias." *Environmental and Resource Economics* 19(4): 383–402.

Converse, J.M. 1976. "Predicting No Opinion in the Polls." *Public Opinion Quarterly* 40: 515-530.

Carson, R.T., W.M. Hanemann, R.J. Kopp, J.A. Krosnick, R.C. Mitchell, S. Presser, P.A. Ruud, K. Smith, M. Conaway, and K. Martin. 1998. "Referendum Design and Contingent Valuation: The NOAA Panel's No-Vote Recommendation." *Review of Economics and Statistics* 80(2): 335 – 338.

Carson, R.T. 2000. "Contingent Valuation: A User's Guide." *Environmental Science and Technology* 34:1413-1418.

Carson, R.T. and T. Groves. 2007. "Incentive and Informational Properties of Preference Questions." *Environmental and Resource Economics* 37(1): 181–210.

Chambers, C.M. and J.C. Whitehead. 2003. "A Contingent Valuation Estimate of the Benefits of Wolves in Minnesota." *Environmental and Resource Economics* 26: 249-267.

Colsher, P.L., and R.B. Wallace. 1989. "Data Quality and Age: Health and Psychobehavioral Correlates of Item Nonresponse and Inconsistent Responses." *Journal of Gerontology* 44(2): 45–52.

Durand, R. M. and Lambert, Z. V. 1988. "Don't Know Responses in Surveys: Analyses and Interpretational Consequences." *Journal of Business Research* 16:169-188.

Faulkenbeny, G.D., and R. Mason. 1978. "Characteristics of Nonopinion and No Opinion Response Groups." *Public Opinion Quarterly* 42(4): 533–543.

Francis, J.B., and J.A. Busch. 1975. "What We Now Know about 'I Don't Knows'." *Public Opinion Quarterly* 39(2): 207–218.

Gelman, A., J. Hill, and M. Yajima. 2012. "Why We (Usually) Don't Have to Worry About Multiple Comparisons." *Journal of Research on Educational Effectiveness* 5(2): 189– 211. https://doi.org/10.1080/19345747.2011.618213.

Greene, W.H. 2012. *Econometric Analysis* (7th edition). Boston, MA: Prentice Hall.

Groothuis, P. A. and Whitehead, J. C. 2002. "Does Don't Know Mean No? Analysis of 'Don't Know' Responses in Dichotomous Choice Contingent Valuation Questions." *Applied Economics* 34: 1935- 1940.

Haab, T. C., and K. E. McConnell. 2002. V*aluing Environmental and Natural Resources: The Econometrics of Non-Market Valuation*. Northampton, MA: Edward Elgar.

Haener, M. K., and W. L. Adamowicz. 1998. "Analysis of 'Don't Know' Response to Referendum Contingent Valuation Questions." *Agricultural and Resource Economics Review* 27(2): 218 – 230.

Hausman, J.A. and D.L. McFadden. 1984. "Specification Tests for the Multinomial Logit Model." *Econometrica* 52: 1219–1240.

Hensher, D.A., J.M. Rose, and W.H. Greene. 2005. *Applied Choice Analysis: A Primer*. New York: Cambridge University Press.

Hensher, D.A. 2010. "Hypothetical bias, choice experiments and willingness to pay." *Transportation Research Part B: Methodological* 44(6): 735–752.

Herriges, J., C. Kling, C.C. Liu, and J. Tobias. 2010. "What Are the Consequences of Consequentiality?" *Journal of Environmental Economics and Management* 59: 67–81.

Hwang, J., D.R. Petrolia, and M.G. Interis. 2014. "Consequentiality and Opt-out Responses in Stated Preference Surveys." *Agricultural and Resource Economics Review* 43(3): 471- 488.

Hwang, J.J. 2024. "Subjective Perceptions about Benefit and Cost Levels in Contingent Valuation." *Agricultural and Resource Economics Review*. Forthcoming.

Interis, M.G. and D.R. Petrolia. 2014. "The Effects of Consequentiality in Binary- and Multinomial-Choice Surveys." *Journal of Agricultural & Resource Economics* 39(2): 1-16.

Krosnick, J.A., and M.A. Milbum. 1990. "Psychological Determinants of Political Opinionation." *Social Cognition* 8(1): 49–72.

List, J.A. 2001. "Do explicit warnings eliminate the hypothetical bias in elicitation procedures? Evidence from field auction for sportscards." *American Economic Review* 91(5): 1498–1507.

Loomis, J. 2011. "What's to know about hypothetical bias in stated preference valuation studies?" *Journal of Economic Surveys* 25(2): 363–370.

Petrolia, D.R., M.G. Interis, and J. Hwang. 2014. "America's Wetland? A National Survey of Willingness to Pay for Restoration of Louisiana's Coastal Wetlands." *Marine Resource Economics* 29(1): 17–37.

Petrolia, D.R., M.G. Interis, and J. Hwang. 2016. "Single-Choice, Repeated-Choice, and Best-Worst Scaling Elicitation Formats: Do Results Differ and by How Much? *Environmental and Resource Economics*: doi:10.1007/s10640-016-0083-6.

Rapoport, R.B. 1981. "The Sex Gap in Political Persuading: Where the 'Structuring Principle' Works." *American Journal of Political Science* 25(1): 32–48.

Rapoport, R.B. 1982. "Sex Differences in Attitude Expression: A Generational Explanation." *Public Opinion Quarterly* 46(1): 86–96.

Ready, R.C., J.C. Whitehead, and G.C. Blomquist. 1995. "Contingent Valuation When Respondents Are Ambivalent." *Journal of Environmental Economics and Management*. 29(2):181-196.

Schuman, H., and S. Presser. 1981. *Questions and Answers in Attitude Surveys: Experiments on Question Form, Wording, and Context*. New York, NY: Academic Press.

Sigelman, C.K., J.L. Winer, and C.J. Schoenrock. 1982. "The Responsiveness of Mentally Retarded Persons to Questions." *Education and Training of the Mentally Retarded* 17(2): 120–124.

StataCorp. 2009. *Stata Release 16*. Statistical Software. College Station, TX: StataCorp LP.

Train, K.E., D.L. McFadden, and M. Ben-Akiva. 1987. "The Demand for Local Telephone Service: A Fully discrete Model of Residential Calling Patterns and Service Choices." *Rand Journal of Economics* 18(1): 109-123.

Train, K.E. 2009. *Discrete Choice Methods with Simulation* (2nd edition). Cambridge University Press, Cambridge

Vossler, C.A., M. Doyon, and D. Rondeau. 2012. "Truth in Consequentiality: Theory and Field Evidence on Discrete Choice Experiments." *American Economic Journal: Microeconomics* 4: 145–71.

Vossler, C. A., and S. B. Watson. 2013. "Understanding the Consequences of Consequentiality: Testing the Validity of Stated Preferences in the Field." *Journal of Economic Behavior & Organization* 86:137–47.

Wang, H. 1997. "Treatment of 'Don't Know' Responses in Contingent Valuation Surveys: A Random Valuation Model." *Journal of Environmental Economics and Management* 32(2): 219 – 232.

Weesie, J. 1999. sg121: Seemingly Unrelated Estimation and the Cluster-adjusted Sandwich Estimator. Stata Technical Bulletin 52: 34–47. Reprinted in *Stata Technical Bulletin Reprints*, vol. 9, pp. 231–248. College Station, TX: StataPress.

Wright, J.R., and R.G. Niemi. 1983. "Perceptions of Candidates' Issue Positions." *Political Behavior* 5(2): 209–223.