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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. We also test empirically whether opt-out responses are more similar to Yes or to No votes and examine the 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, don't know option, opt-out option, random utility model

Introduction

In 1993, the National Oceanic and Atmospheric Administration (NOAA) appointed a panel of prominent social scientists, led by Kenneth Arrow, to assess the 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; 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 (i.e., "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%, Arrow et al., 1993; 36%, Groothuis and Whitehead, 2002; 18%, Haener and Adamowicz, 1998; and 30%, Wang, 1997). Second, as Wang (1997) pointed out, discarding such responses implicitly assumes that the 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; Faulkenberry and Mason, 1978; Durand and Lambert, 1988; Krosnick and Milburn, 1990; Rapoport, 1981; Wright and Niemi, 1983) are less likely to opt out. Also, respondents who have higher levels of education (Bishop, Oldendick, and Tuchfarber, 1980; Schuman and Presser, 1981); higher cognitive skills (Sigelman, Winer, and Schoenrock, 1982; Colsher and Wallace, 1989); and who are younger, male, white, and/or wealthier

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(Francis and Busch, 1975; Converse, 1976; Rapoport, 1982) are less likely to opt out. Therefore, there is empirical evidence that the practice of discarding opt-out choices 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 in which one version included the opt-out option and the other did not; they found that including the opt-out option did not significantly change the proportion of Yes votes, implying that respondents who opted out would have chosen No if the opt-out option had not been 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 a willingness-to accept (WTA) setting. Balcombe and Fraser (2009) found that opt-out responses are more similar to Yes than to 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) examined effects of consequentiality on opt-out empirically. Consequentiality is the perception that respondents believe that their choices in the survey will affect the policy outcome and is a condition for respondents to reveal their true preferences (Carson and Groves, 2007). A survey question is consequential if the respondent believes their response will affect some outcome that they care 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 to be 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 (i) to examine theoretically why respondents opt out; (ii) to test our theoretical findings empirically; (iii) to test empirically whether opt-out is similar to Yes or to No; and (iv) to examine consequences of discarding opt-out responses. For the empirical analysis, we use datasets from two different CV surveys, both of which focused on coastal wetlands in the Gulf of Mexico region (Louisiana and Florida) and included an opt-out option in the referendum. The opt-out option was identically labeled ("I prefer not to vote") in both cases. Following the literature (e.g., Carson et al., 1998; Haener and Adamowicz, 1998; Groothuis and Whitehead, 2002; Chambers and Whitehead, 2003; Hwang, Petrolia, and Interis, 2014), we first treat opt-out as a distinct alternative to Yes and No. Although several studies have tested whether opt-out is similar to Yes or to 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: parameter estimates, sample means, and WTP estimates. We find that respondents with well-defined preferences (i.e., those who know which option they prefer) will still opt out if they perceive the survey to be 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 the choice that a respondent makes is consistent with their 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, the 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: (i) a respondent chooses Yes, and the program is implemented; (ii) a respondent chooses Yes, and the program is not implemented; (iv) a respondent chooses No, and the program is implemented; and (iv) 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, policy makers' 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

$$EU_{iyes} = \tilde{p}_{iyes} \times U_{iP} + \left(1 - \tilde{p}_{iyes}\right) \times U_{iNP}, \tag{1}$$

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

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

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

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

Carson and Groves (2007, p. 183) argued that

> If 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.

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: (i) a respondent chooses Yes, and the program is implemented; (ii) a respondent chooses Yes, and the program is not implemented; (iii) a respondent chooses No, and the program is implemented; (iv) a respondent chooses No, and the program is not implemented; (v) a respondent chooses to opt out, and the program is implemented; and (vi) a respondent chooses to opt out, and the program is not implemented.

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

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

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 equation (4) from equation (1) yields

$$\begin{aligned} EU_{iyes} - EU_{ioptout} &= \tilde{p}_{iyes} \times U_{iP} + \left(1 - \tilde{p}_{iyes}\right) \times U_{iNP-} - \tilde{p}_{ioptout} \times U_{iP} - \left(1 - \tilde{p}_{ioptout}\right) \times U_{iNP} \\ &= \left(\tilde{p}_{iyes} - \tilde{p}_{ioptout}\right) \times (U_{iP} - U_{iNP}) > 0 \end{aligned} \tag{5}$$

The first term, $\left(\tilde{p}_{iyes} - \tilde{p}_{ioptout}\right) > 0$, implies that $EU_{iyes} - EU_{ioptout} > 0$ 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 $EU_{ino} - EU_{ioptout} > 0$.

$$\begin{aligned} EU_{ino} - EU_{iyes} &= \tilde{p}_{ino} \times U_{iP} + (1 - \tilde{p}_{ino}) \times U_{iNP} - \tilde{p}_{iyes} \times U_{iP} - \left(1 - \tilde{p}_{iyes}\right) \times U_{iNP} \\ &= \left(\tilde{p}_{ino} - \tilde{p}_{iyes}\right) \times (U_{iP} - U_{iNP}) > 0. \end{aligned} \tag{6}$$

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

$$\begin{aligned} EU_{ino} - EU_{ioptout} &= \tilde{p}_{ino} \times U_{iPP} - (1 - \tilde{p}_{ino}) \times U_{iNPP} - \tilde{p}_{ioptout} \times U_{iP} + \left(1 - \tilde{p}_{ioptout}\right) \times U_{iNP} \\ &= \left(\tilde{p}_{ino} - \tilde{p}_{ioptout}\right) \times (U_{iP} - U_{iNP}) > 0. \end{aligned} \tag{7}$$

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

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

$$\begin{aligned} EU_{ioptout} - EU_{iyes} &= \tilde{p}_{ioptout} \times U_{iP} + \left(1 - \tilde{p}_{ioptout}\right) \times U_{iNP} - \tilde{p}_{iyes} \times U_{iP} - \left(1 - \tilde{p}_{iyes}\right) \times U_{iNP} \\ &= \left(\tilde{p}_{ioptout} - \tilde{p}_{iyes}\right) \times (U_{iP} - U_{iNP}) > 0. \end{aligned} \tag{8}$$

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

$$\begin{aligned} EU_{ioptout} - EU_{ino} &= \tilde{p}_{ioptout} \times U_{iP} + \left(1 - \tilde{p}_{ioptout}\right) \times U_{iNP} - \tilde{p}_{ino} \times U_{iP} - (1 - \tilde{p}_{ino}) \times U_{iNP} \\ &= \left(\tilde{p}_{ioptout} - \tilde{p}_{ino}\right) \times (U_{iP} - U_{iNP}) > 0. \end{aligned} \tag{9}$$

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

There are two cases in which a respondent chooses to 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 Arrow et al. (1993, p. 34) pointed out "rough indifference between a yes and a no vote" as a reason for opting out. The second case is when the strict inequality between perceived probabilities assumption does not hold, such that the difference between perceived probabilities is 0 in equations (8) and (9), and the respondent is 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 has to do with 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 0, 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

Louisiana 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, that sampled respondents from a probability-based panel that is representative of the target population (noninstitutionalized adults at least 18 years of age residing in the United States). The survey had two versions: a binary CV and a multinomial discrete choice experiment. This analysis uses only the CV version.[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, and how much of them have been lost due to natural erosion, sea-level rise, sinking of land, winds, tides, currents, storms, and human development. Then it proposed a large-scale (234,000 acres) restoration project that would 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 presented as a one-time tax and one of nine dollar values was assigned at random: $25, $90, $155, $285, $545, $925, $1,305, $2,065, $2,825. Respondents were asked to evaluate the proposed project at the given cost and to cast their votes. To ensure incentive compatibility for those who perceived 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%), 400 chose No (29%), and 350 chose opt-out (26%).

Perceived consequentiality was measured based on two survey questions:

> *When voting, how important did you think **your vote** 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 **this survey** 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.*

The first question elicited respondent perceptions about the importance of their vote, while the second question elicited respondent perceptions about the likelihood that the 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 policy-making 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. Hwang, Petrolia, and Interis (2014) previously examined empirical effects of consequentiality on opt-out, but they used 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

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

wetland and barrier island loss issue in coastal Louisiana; = 0 otherwise), income, age, race ("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).

Florida 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 noninstitutionalized 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, and respondents were representative of the population demographics in terms of age, gender, race, education, and income. After providing detailed information about wetlands and the ecosystem services they provide—such as wildlife habitats, fisheries support, storm surge protection, and improved water quality—the survey described the amount of wetlands 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 presented as a one-time tax and was chosen at random from a set of five cost options—$50, $300, $650, $950, $1,200. The cost was described as a one-time fee that would be added to one's 2021 federal income tax return. A total of 7,483 who were on the Qualtrics panel were invited to take the survey, 4,146 responded to the survey, and 1,243 completed responses were provided by Qualtrics after screening for demographic quotas and quality control (e.g., speed-takers, bots). Of the 1,243 respondents, 798 voted Yes (64%), 259 voted No (21%), and 186 opted out in the referendum (15%).

Survey questions to elicit perceived consequentiality were almost identical to those from the previous survey. One question asked respondents 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. While the questions in the previous survey measured perceptions using Likert scales, the questions in this survey measured 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 ranged from 0 to 20. Finally, other demographic variables used in the analysis included income, age, race ("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

$$\text{Prob}\left(Y_i = j \mid \boldsymbol{x}_i\right) = \frac{\exp\left(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\right)}{\sum_{j=0}^{J}\exp\left(\boldsymbol{x}'_i\boldsymbol{\beta}_j\right)}, \text{ where} j = 0, 1, \ldots, J, \tag{10}$$

where $\boldsymbol{x}'_i$ is a vector of individual-specific characteristics—including cost—that is exogenously assigned to respondents and $\boldsymbol{\beta}_j$ is a vector of parameter estimates (Greene, 2012). The multinomial logit model is estimated treating opt-out as an alternative along with Yes or No.

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

Consequentiality and Opt-Out

Our hypothesis is that inconsequential respondents are more likely to choose to opt out. Note that parameter estimates resulting from the multinomial logit model are relative to the base alternative (No). This results in two separate subhypotheses to test effects of consequentiality on opt-out. $H1_{optout} : \beta_{consequential,\ optout} < 0$ indicates that consequential respondents are less likely to choose to opt out than to choose No, or inconsequential respondents are more likely to choose to opt out than to choose No. $H_{1yes} : \beta_{consequential,\ yes} > \beta_{consequential,\ optout}$ indicates that consequential respondents are more likely to choose Yes than opt-out, or inconsequential respondents are more likely to choose to opt out than to choose Yes.

Is Opt-Out Similar to Yes or to No?

We examine whether opt-out is similar to Yes or to No based on two criteria: beta estimates and the scale parameter. We first test whether beta estimates between (i) opt-out and Yes and (ii) opt-out and No are equal ($H_{2Y} : \boldsymbol{\beta}_{optout} = \boldsymbol{\beta}_{yes}; H_{2N} : \boldsymbol{\beta}_{optout} = \boldsymbol{\beta}_{no}$). 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 to 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 (*i.i.d.*). Due to the *i.i.d.* 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

$$(11) \qquad P_{ijk} = \frac{\exp\left\{\left(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\right)/\lambda_k\right\}\left[\sum_{j\in B_k}\exp\left\{\left(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\right)/\lambda_k\right\}\right]^{\lambda_k-1}}{\sum_{l=1}^{K}\left[\Sigma_{j\in B_l}\exp\left\{\left(\boldsymbol{x}'_{ij}\boldsymbol{\beta}_j\right)/\lambda_l\right\}\right]^{\lambda_l}},$$

where λ_k is the scale parameter for a branch k. The scale parameter must lie within the 0–1 range; $\lambda_k = 0$ indicates 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, 2009). Further, $0 < \lambda_k < 1$ indicates that substitution between alternatives is greater than substitution between nests. As discussed earlier, the nested logit is typically estimated to relax the IIA property. For example, Petrolia, Interis, and Hwang (2018) relaxed the IIA property by nesting proposed program alternatives (against no) using data from a discrete choice experiment. In this paper, however, we adopt the nested logit model to test whether opt-out is similar to Yes or to No. Two sets of nested logit regressions are estimated. Table 1 describes the nest structure for two models. Nest-Yes hypothesizes that opt-out is similar to Yes ($H_{3Y} : 0 < \lambda_{yes} < 1$) and, and Nest-No hypothesizes that opt-out is similar to No ($H_{3Y} : 0 < \lambda_{no} < 1$). 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.

Table 2. Summary Statistics

	Louisiana Wetlands Sample		Florida Wetlands Sample	
	Excluding Opt-Outs	**Including Opt-Outs**	**Excluding Opt-Outs**	**Including Opt-Outs**
Variable	**(N = 1,008)**	**(N = 1,358)**	**(N = 1,057)**	**(N = 1,243)**
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)

Notes: Values in parentheses are standard deviations.

Consequences of Discarding Opt-Out

We examine the consequences of discarding opt-out based on three criteria: parameter estimates, sample means, and WTP. First, we test whether parameter estimates between two samples are equal ($H_4 : \hat{\boldsymbol{\beta}}_2 = \hat{\boldsymbol{\beta}}_3$), where the subscripts represent the number of alternatives. Hausman and McFadden (1984) proposed a test (i.e., the 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

$$\chi_k^2 = \left(\widehat{\boldsymbol{\beta}}_2 - \widehat{\boldsymbol{\beta}}_3\right)' \left[\text{var}\left(\widehat{\boldsymbol{\beta}}_2 - \widehat{\boldsymbol{\beta}}_3\right)\right]^{-1} \left(\widehat{\boldsymbol{\beta}}_2 - \widehat{\boldsymbol{\beta}}_3\right), \tag{12}$$

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 (2000) proposed an alternative specification that overcomes the limitation of the Hausman test. The Hausman test estimates $\text{var}\left(\widehat{\boldsymbol{\beta}}_2 - \widehat{\boldsymbol{\beta}}_3\right)$ by $\text{var}\left(\widehat{\boldsymbol{\beta}}_2\right) - \text{var}\left(\widehat{\boldsymbol{\beta}}_3\right)$, whereas the alternative test uses $\text{var}\left(\widehat{\boldsymbol{\beta}}_2\right) - 2 \times \text{cov}\left(\widehat{\boldsymbol{\beta}}_2,\widehat{\boldsymbol{\beta}}_3\right) + \text{var}\left(\widehat{\boldsymbol{\beta}}_3\right)$, such that the test statistic is always well defined (StataCorp, 2019). We use the "Hausman-type" test using Stata's "suest" routine (StataCorp, 2019).

Second, we test whether sample means between two samples are equal ($H_5 : \bar{z}_2 = \bar{z}_3$). 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

$$T^2 = (\bar{z}_2 - \bar{z}_3)\, \hat{\boldsymbol{v}}^{-1} (\bar{z}_2 - \bar{z}_3)', \tag{13}$$

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

$$F_{k,n_2+n_3-1} = \frac{(n_2 + n_3 - k - 1\}}{(n_2 + n_3 - 2\}\, k} \times T^2, \tag{14}$$

where n_2 and n_3 represent the number of observations for samples 2 and 3. Table 2 presents summary statistics for samples 2 and 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. Finally, we 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

$$E\left(WTP_s\right) = -\frac{\hat{\boldsymbol{\beta}}_s^*}{\hat{\beta}_{cost,\,s}} \times \bar{z}_s, \tag{15}$$

where $s = \{2,3\}$, where 2 and 3 refer to sample 2 and sample 3, respectively; $\hat{\beta}_{cost,\,s}$ is an estimated parameter for cost for sample s; $\hat{\boldsymbol{\beta}}_s^*$ is a vector of parameter estimates for sample s except the estimated parameter for cost; and $\bar{z}_s$ is a vector of sample characteristics included in regression evaluated at mean (Haab and McConnell, 2002). Confidence intervals are calculated using the Delta method (Greene, 2012). We test whether the two samples yield the same WTP estimates; $H_6 : E\left(WTP_2\right) = E\left(WTP_3\right)$ based on the two-sample z-test using the asymptotic variance of WTP for two samples resulting 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 Louisiana wetlands and Florida 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.

Consequentiality and Opt-Out

As discussed earlier, we have two subhypotheses to test the relationship between consequentiality and opt-out. The Louisiana 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 to opt out than to choose No, or, said differently, inconsequential respondents are more likely to choose to opt out than to choose 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 Florida 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.

Table 3. Louisiana Wetlands Regression Results

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

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Is Opt-Out Similar to Yes or to No?

Let us first focus on whether opt-out is similar to Yes or to 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 Louisiana 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 Florida wetlands, the Wald statistics, χ^2_8, for H_{2Y} and H_{2N} are 115.45 and 19.44, respectively. Therefore, we reject both at the 5% 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). The Louisiana wetlands

Table 4. Florida Wetlands Regression Results

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

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

model includes 10 parameters, and the Florida wetlands model includes 8 parameters, which means 10 and 8 subhypotheses, respectively, are being tested for the equality test as vectors. Bonferroni correction suggests that the confidence level (a) for a multiple comparison test should be adjusted as a/m, where m is the number of subhypotheses (Gelman, Hill, and Yajima, 2012). The confidence level with the correction becomes $0.05/10 = 0.005$ for the Louisiana wetlands model and $0.05/8 = 0.00625$ for the Florida wetlands model. Given that the p-value for both H_{2Y} and H_{2N} is 0.0000 for the Louisiana wetlands model, we still reject the nulls with the correction. As for the Florida wetlands model, the p-values for H_{2Y} and H_{2N} are 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-

Table 5. Willingness to Pay Estimates

Data	Including Opt-Outs	Excluding Opt-Outs
Louisiana Wetlands Sample	\$1,370.07 (\$1,069.56, \$1,670.58)	\$1,424.31 (\$1,128.36, \$1,720.26)
Florida Wetlands Sample	\$3,530.37 (\$1,075.27, \$5,985.47)	\$3,594.75 (\$1,174.48, \$6,015.03)

Notes: Values in parentheses are 95% confidence intervals.

out and yes. For the Louisiana wetlands model, the likelihood ratio test statistic $\chi_1^2 = 5.48$ 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. A 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 the Florida wetlands model, the scale parameter is within the correct range but is not statistically significant ($\chi_1^2 = 0.84$).

Nest-No hypothesizes that opt-out is similar to No. For the Louisiana wetlands model, the scale parameter, λ_{NA} is outside the range, and the likelihood ratio test statistic $\chi_1^2 = 1.95$ indicates that we fail to reject $\lambda_{NA} = 1$. For the Florida wetlands model, the scale parameter is also outside the range and is not significant ($\chi_1^2 = 0.74$). 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 the Louisiana wetlands model, $\chi_{11}^2 = 11.58$ indicates that we fail to reject H_4. For the Florida wetlands model, $\chi_9^2 = 6.62$ 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 $H_5 : \bar{z}_2 = \bar{z}_3$. For the Louisiana wetlands model, 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 samples 2 and 3 are statistically different for the Louisiana wetlands model. For the Florida wetlands model, 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 the Florida wetlands model.

Table 5 presents WTP estimates from the multinomial logit model for sample 3 and the logit model for sample 2. For the Louisiana wetlands model, 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 the Florida wetlands model, 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

Table 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.

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

	Louisiana Wetlands Sample		Florida Wetlands Sample	
Variables	**Yes**	**Opt-Out**	**Yes**	**Opt-Out**
Cost	−0.001***	0.000	−0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Consequential	1.230*	−0.515	0.275***	0.125
	(0.700)	(0.861)	(0.069)	(0.082)
Familiar	0.026	−0.680***		
	(0.189)	(0.212)		
Income	0.000	−8.13E − 06***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.006	0.016***	−0.026*	−0.005
	(0.005)	(0.005)	(0.016)	(0.017)
White	−0.190	−0.893***	1.007*	0.416
	(0.221)	(0.212)	(0.581)	(0.639)
Bachelor's degree	−0.104	−0.622***	−0.518	−0.669
	(0.195)	(0.216)	(0.594)	(0.708)
Male	−0.285*	−0.302*	1.139**	0.955*
	(0.173)	(0.176)	(0.482)	(0.530)
Married	−0.581***	−0.088		
	(0.185)	(0.191)		
Conservative	−0.230***	−0.173***	−0.027	0.072
	(0.055)	(0.056)	(0.081)	(0.092)
Consequential×Familiar	0.641**	0.837**		
	(0.327)	(0.426)	(0.000)	(0.000)
Consequential×Income	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Consequential×Age	0.014	0.010	0.000	0.000
	(0.010)	(0.012)	(0.001)	(0.001)
Consequential×White	−0.244	−0.123	−0.092**	−0.064
	(0.390)	(0.460)	(0.045)	(0.053)
Consequential×Bachelor	0.202	0.341	0.045	0.014
	(0.350)	(0.468)	(0.046)	(0.060)
Consequential×Male	0.445	0.005	−0.097**	−0.109**
	(0.310)	(0.399)	(0.038)	(0.045)
Consequential×Married	−0.021	−0.649		
	(0.337)	(0.427)		
Consequential×Conservative	−0.218**	−0.224	−0.005	−0.010
	(0.111)	(0.138)	(0.006)	(0.007)
Constant	1.568***	1.673***	−0.649	−0.472
	(0.380)	(0.387)	(0.843)	(0.937)
Log-likelihood	−1, 243.585	−981.725		

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

The estimated parameter for the interaction term between consequentiality and familiarity with the topic for the Louisiana wetlands model 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 to choose No, or, alternatively, those who are consequential but unfamiliar with the topic are less likely to choose Yes and opt-out than to choose 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 to opt out than to choose No, or alternatively, those who are inconsequential and unfamiliar with the topic are more likely to choose to opt out than to choose 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 0).

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 the Louisiana wetlands model, indicating that those who are inconsequential and have a bachelor's degree are less likely to choose to opt out, or alternatively, those who are inconsequential and do not have a bachelor's degree are more likely to choose to opt out.[2] 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 not to 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 in which 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 the reason Arrow et al. (1993) suggested 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 the Arrow et al. 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 to 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 to 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 to No, it is inconsequentiality that is likely to cause expected utilities to be the same regardless of their preferences.

[2] $\beta_1 Bachelor + \beta_2 Consequential \times Bachelor$ is equivalent to $-\beta_1 NoBachelor - \beta_2 Consequential \times NoBachelor$.

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 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 choose 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 the 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 whether 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 to which stated preference methods are subject, such as hypothetical bias. No actual payments were made as a result of their choice in the referendum. Respondents' decision to choose to 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. Further, 5,185 people were invited to take either the binary CV or multinomial discrete choice experiment 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; therefore, the exact survey response rate specific to our analysis is not available. For the Florida wetlands survey, 7,483 people were invited, and 4,146 responded. However, our analysis utilized only the 1,243 observations provided by Qualtrics after screening for demographic quotas. We acknowledge potential sample-selection bias associated with the data collection; the proportion of those who choose to 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 (e.g., consequentiality) have emerged, this study finds a new reason to use opt-out that was not identified at the time of Arrow et al. Given our finding, we want to remind researchers to use the option as recommended by Arrow et al. and use it correctly. Further, 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 to No. We hope to see more research utilizing the model in analyzing opt-out responses.

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