# Mitigating Hypothetical Bias In Stated Preference Data: Evidence From Sports Tourism

By: **John C. Whitehead**, Melissa S. Weddell, & **Peter A. Groothuis**

**Abstract**

One of the major criticisms of stated preference data is hypothetical bias. Using a unique dataset of both stated and actual behavior, we test for hypothetical bias of stated preference survey responses. We consider whether respondents tend to overstate their participatory sporting event behavior ex ante when compared to their actual behavior at different registration fees. We find that stated behavior accurately predicts actual behavior at a middle level of respondent certainty, overpredicts actual behavior at a lower level of certainty, and underpredicts behavior at a higher level of certainty. This result suggests that respondent uncertainty corrections can be used to mitigate hypothetical bias and stated preference data can be used to better understand actual behavior in situations where no data exist.

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# MITIGATING HYPOTHETICAL BIAS IN STATED PREFERENCE DATA: EVIDENCE FROM SPORTS TOURISM

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*One of the major criticisms of stated preference data is hypothetical bias. Using a unique dataset of both stated and actual behavior, we test for hypothetical bias of stated preference survey responses. We consider whether respondents tend to overstate their participatory sporting event behavior ex ante when compared to their actual behavior at different registration fees. We find that stated behavior accurately predicts actual behavior at a middle level of respondent certainty, overpredicts actual behavior at a lower level of certainty, and underpredicts behavior at a higher level of certainty. This result suggests that respondent uncertainty corrections can be used to mitigate hypothetical bias and stated preference data can be used to better understand actual behavior in situations where no data exist.*

## I. INTRODUCTION

The contingent valuation method (CVM) elicits statements of hypothetical willingness-to-pay. In a recent symposium on contingent valuation in the *Journal of Economic Perspectives*, Kling, Phaneuf, and Zhao (2012) provide a balanced overview and Carson (2012) argues that the CVM is "a practical alternative when prices aren't available." In stark contrast, Hausman's (2012) opinion on CVM has gone from "dubious to hopeless" in its ability to measure the value accurately.[1] One of Hausman's (2012) three issues with contingent valuation is "hypothetical response bias that leads contingent valuation to overstatements of value." To test for hypothetical bias, most studies use some form of the stylized null hypothesis that stated preference responses are equal to actual behavior when money or some other real outcome is at stake. If the hypothesis is rejected, the stated preference study suffers from hypothetical bias.

Several meta-analyses compare value estimates from stated and actual choices. List and Gallet (2001) and Little and Berrens (2004) find that values based on hypothetical willingness-to-pay and willingness-to-accept statements are about three times higher than those based on real choices. Murphy et al. (2005), using only the willingness-to-pay data, find hypothetical values are about 1.35 times higher than those based on real choices. All of the meta-analyses studies evaluate lab and field experimental data before hypothetical bias mitigation approaches were used extensively. When hypothetical bias remains, there are several approaches to hypothetical bias mitigation in contingent valuation (Loomis 2011). Champ and Bishop (2001) find that respondents who rate themselves, at least, seven of ten on a certainty scale on a voluntary contribution question behave similarly when faced with the actual choice. Blumenschein et al. (2008) employ a qualitative certainty scale and find that respondents who are "very certain" about their hypothetical choice behave similarly in the actual setting. Carson and Groves (2007)

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1. Haab et al. (2013) more thoroughly review the literature and argue that Hausman's "selective" review misses evidence supporting the ability of stated preference data to provide useful information.

**ABBREVIATIONS**

BSG: Blood Sweat and Gears
CVM: Contingent Valuation Method

argue that consequential contingent valuation surveys will not suffer from hypothetical bias. Landry and List (2007) find no hypothetical bias when responses are consequential in a field experiment. Vossler and Watson (2013) find no hypothetical bias when comparing stated and actual referendum votes for respondents who believe the survey is consequential.

In the contingent behavior literature, there have been two test-retest studies where no hypothetical bias is found. Loomis (1993) compares stated length of stay on recreation trips collected at a lake with a hypothetical water level versus actual length of stay when the hypothetical water level was realized and finds no statistically significant difference. Grijalva et al. (2002) find that stated preference rock climbing trips fall with a hypothetical closure of rock climbing areas. When the areas are subsequently closed, actual trips differ in the expected direction and by similar magnitudes.[2] Whitehead et al. (2008) argue that combining revealed and stated preference data can be used to mitigate hypothetical bias in contingent behavior data. For example, Whitehead (2005) and Whitehead, Noonan, and Marquardt (2014) find that survey respondents overstate their future behavior.[3] Using jointly estimated revealed and stated preference data models, a common hypothetical bias correction yields statistically equivalent predictions of the actual behavior in both studies. Overall, the results of the more recent contingent valuation and behavior studies suggest that hypothetical bias can occur under some circumstances but there are methods to mitigate the effect.

We use a blend of the contingent valuation and behavior methods to estimate the demand for a sports tourism event and consider whether hypothetical bias can be mitigated by using an intensity of preference correction. We conduct surveys of participants of a popular organized bike ride in 2011 and 2012. In 2011, we ask riders if they would participate in the 2012 ride at the current registration fee and ask about willingness-to-pay higher registration fees. In 2012, the registration fee was increased by $10. Using these data, we conduct nonparametric and parametric tests for hypothetical bias at different levels of respondent certainty. We then combine revealed and stated preference data in a fixed effects probit model and find that hypothetical bias can be mitigated. Our results provide evidence that hypothetical questions are "a practical alternative when prices aren't available" and are neither "hopeless" nor "dubious."

2. The test-retest studies are inherently different than tests of convergent validity of revealed and stated preference data where comparisons are made at a single point in time (e.g., Dickie, Fisher, and Gerking 1987; Jeon and Herriges 2010; Whitehead et al. 2010).

3. See also Atkinson and Whitehead (2015) who find a similar magnitude of hypothetical bias but are not able to mitigate the bias with joint estimation due to data limitations.

## II. METHODS

Our data are from "Blood Sweat and Gears" (BSG), a participatory bicycle sporting event.[4] The BSG includes 50- and 100-mile bike rides (the organizers insist on calling it a ride, but many participants are racing) in and around mountain communities in Watauga County, NC, including the Blue Ridge Parkway. Participation in the BSG is constrained with a limit of 1,250 riders on the Blue Ridge Parkway placed by the National Park Service. Ninety-three riders were on the 2011 waiting list and 456 were on the 2012 waiting list.[5] Demand data were gathered by surveys that were emailed to registered riders after the 2011 BSG. Of the 1,156 registered riders with useable email addresses, 561 completed the survey after three mailings. The response rate is 48%. In 2012, 611 riders completed the survey from 1,135 useable email addresses for a 54% response rate. Deleting duplicate email addresses from each year (i.e., multiyear and multifamily participants), the sample size used for analysis is 1,923 participants. Of these, 60% participated in 2011 and 61% participated in 2012. A total of 21% participated in both years.

In the 2011 survey, respondents were told: "Proceeds from the 2012 ride will benefit two charities established by the Watauga County Chapter of the American Red Cross. The Jeremy Dale Fisher Fund and The Russell Fund provide assistance to local families that are displaced by fire, flood or similar disasters." Respondents who stated that they intended to participate in the 50-mile ride received the 50-mile ride question: "The 50-mile route has a limit of 500 riders and sold out in a week in 2011." Respondents who stated that they intended to participate in the 100-mile ride received a similar version: "The 100-mile route has a limit of 750 riders and sold out in one day in 2011." The stated preference

4. See the website for details: http://www.bloodsweatandgears.org.

5. The 2014 BSG sold out in 16 minutes with 4,000 potential riders attempting to register for 1,250 spots.

scenario is a higher entrance fee: "One proposal being considered is to charge a higher entrance fee in order to provide even more assistance to local families. Would you be willing to pay the following entrance fees for the 2012 ride if you knew all of the additional funds went to charity?" Respondents were presented with a response table. In the left-hand-side column were five entrance fees, $60, $70, $80, $90, and $100. The top row contained five responses, "definitely no," "probably no," "not sure," "probably yes," and "definitely yes." Respondents checked a box in each entrance fee row to indicate their intention to participate at different fees (see Appendix S1, Supporting Information). The registration fee in 2011 was $60.

## III. HYPOTHETICAL BIAS MITIGATION

Previous research has found that recoding uncertain positive stated behavior responses (e.g., "for," "yes," or "would purchase") to negative responses (e.g., "against," "no," or "would not purchase") more closely aligns stated with actual behavior (e.g., Blumenschein et al. 2008; Champ and Bishop 2001). In this context, recoding may better account for respondents who are uncertain about their demand and would not actually donate or purchase the good in a real situation. In the current context, there may be more uncertainty in the stated behavior data than in previous CVM applications. The stated behavior was elicited 6 months ahead of the 2012 BSG registration date and almost a full year ahead of the participation date. Given that the BSG requires preparation and rigorous, injury free training, many respondents may be relatively certain that they are willing to participate but relatively uncertain if they will be able to participate. Furthermore, respondents may be willing and able to participate at the time of registration but unable to register given the derby-style online process. As such, we investigate alternative recodings of the stated preference variable.

Carson and Groves (2007) argue that respondents will answer valuation questions truthfully if they consider the survey to be consequential and the value elicitation question is incentive compatible. A consequential survey has a nonzero probability of influencing a real outcome. The BSG post-ride survey is expected to be consequential because each respondent knew that it was being conducted for the BSG organizers who would likely consider the results when planning the 2012 event. On the first page of the survey, respondents are told that "the information gathered in this study will help the Blood Sweat and Gears Committee better organize future rides." We assume that all respondents considered the survey consequential because we did not ask a consequentiality debriefing question as has been carried out in other studies (e.g., Vossler and Watson 2013).

The willingness-to-pay question is incentive compatible for some respondents but not others which may allow for strategic behavior. Those who are willing to pay more for registration will respond truthfully positively to the participation question. This will influence organizers to raise fees, reduce the pool of riders, and increase the probability of a successful registration. Those respondents who are not willing to pay a higher registration fee but intend to register also have an incentive to truthfully respond negatively when faced with the higher fees.

The willingness-to-pay question provides opportunities for other respondents to behave strategically in one of two ways. Participants who are not willing to pay higher fees and relatively negative about their future participation may respond strategically positive to higher fees. Those participants who would like for BSG charitable donations to increase would respond strategically by indicating participation knowing that they will not have to pay the extra fee. To minimize this effect, we do not ask the higher fee question to those who state that they will definitely not participate in 2012 at the current fee. Second, consider those who intend to participate and might be willing to pay more but want to influence organizers to keep fees low. Those respondents who are willing to risk not being able to register due to the larger pool of registrants will respond strategically negative to the participation question in order to try to influence organizers to keep fees low.

## IV. RESULTS

Each respondent could answer up to five stated preference questions but some of these responses are redundant. A redundant response is one in which the respondent states that they would definitely pay an even higher amount or would definitely not pay an even lower amount. For example, if the respondent would definitely pay $60 and $70 we discard the $60 response. If the respondent would definitely not pay $90 and $100, we discard the $100 response. We include all respondents who answered at least

**TABLE 1**
Revealed and Stated Preference Participation Data

| Year | Cases | Stated Preference | Fee | Participation: Definitely Yes (%) | Definitely and Probably Yes (%) | Definitely Yes, Probably Yes, and Not Sure (%) |
|---|---|---|---|---|---|---|
| 2011 | 1,923 | 0 | 60 | 59.85 | | |
| 2012 | 316 | 1 | 60 | 55.70 | 89.87 | 98.42 |
| 2012 | 412 | 1 | 70 | 22.33 | 66.26 | 84.47 |
| 2012 | 383 | 1 | 80 | 5.74 | 31.85 | 63.97 |
| 2012 | 332 | 1 | 90 | 0.60 | 15.06 | 43.67 |
| 2012 | 305 | 1 | 100 | 15.41 | 26.23 | 49.51 |
| 2012 | 1,923 | 0 | 70 | 60.89 | | |

one nonredundant stated preference question. A total of 16% ($n = 79$) of the sample of 501 provides one stated preference question response, 8% provides two ($n = 42$), 17% provides three ($n = 83$), 30% provides four ($n = 149$), and 30% of the sample ($n = 148$) provides five stated preference responses.

The total number of stated preference responses is 1,748 with between 54% and 73% of the sample of 501 answering stated preference questions at each entrance fee (Table 1). In general, the responses exhibit rationality with the percentage of "definitely yes" responses falling from 56% to 15% as the fee rises from \$60 to \$100. Our study allows a test of hypothetical bias because the entrance fee for the BSG was raised from \$60 to \$70 in 2012. Each respondent's answer to the \$70 entrance fee question and intention to ride the 50- or 100-mile route can be compared with their actual registration behavior in the 2012 ride. For this analysis, we include redundant responses to facilitate a direct comparison. For example, if the survey respondent answered "definitely yes" to a registration fee of \$80, we include them as a "definitely yes" at the \$60 and \$70 fees.

Two hundred and twelve 2011 survey respondents actually registered for the 2012 BSG. In our sample, 33% answered "definitely yes" and 69% answered "probably yes" to the 2012 BSG participation question with a \$70 entrance fee. These responses provide upper and lower bounds to the actual return participation of 42% for the 2011 sample. In contrast, 68% of respondents state that they will definitely participate at the \$60 entrance fee while 93% would probably participate. At the \$80 entrance fee, only 14% state that they will definitely participate and 35% state that they would probably participate. The aggregate stated preference data provide evidence of predictive validity. Stated preferences at the \$70 entrance fee are more accurate than the stated preferences at the \$60 and \$80 entrance fees when predicting actual behavior at the \$70 fee.

When we consider individual predictions at the \$70 fee with the "definitely yes" response for 501 participants with stated preference data, 14% of respondents successfully predicted their own participation and 39% successfully predicted their nonparticipation. Although 29% stated that they definitely would not participate but did, 19% stated that they definitely would participate and did not. When we consider individual predictions with the "probably yes" response, 30% of respondents successfully predicted their own participation and 19% successfully predicted their nonparticipation at the \$70 fee. Although 12% stated that they probably would not participate but did, 39% stated that they probably would participate and did not.

## V. EMPIRICAL MODEL

In this section, we describe the empirical model to estimate the ability of stated preference behavior data to predict actual behavior. Conceptually, the categorical response, $y_i$, to the registration fee participation question depends on whether willingness-to-pay is greater than the registration fee. Because we have no individual-specific information from survey nonrespondents and pseudo-panel data, from two to seven revealed and stated preference responses for each respondent, we estimate a fixed effects panel probit, $\pi\left[y_{it}^{z} = 1\right] = \phi\left(\alpha_i + \beta' x_{it}\right)$, where $y_{it}^{z}$ is the participation response, $z$ is the participation threshold, $\alpha_i$ is the individual-specific fixed effect, $\beta$ is the coefficient vector, $x_{it}$ is a vector of independent variables (registration fee and a

**TABLE 2**
Fixed Effects Probit Participation Models

| | Definitely | | Definitely and Probably | | Definitely, Probably, and Not Sure | |
|---|---|---|---|---|---|---|
| | **Coeff.** | ***SE*** | **Coeff.** | ***SE*** | **Coeff.** | ***SE*** |
| FEE | −.0415* | .0028 | −.0576* | .0026 | −.0503* | .0026 |
| SP | −1.119* | .0678 | .012 | .0671 | .663* | .0728 |
| Log-likelihood function | −2,859.55 | | −3,007.88 | | −2,940.81 | |
| Akaike Information Criterion | 9,147.10 | | 9,407.80 | | 9,207.60 | |
| Marginal fee effect | −.0153 | | −.0229 | | −.0199 | |
| Fee elasticity | −3.10 | | −3.48 | | −2.54 | |
| Sample size | 5,594 | | 5,594 | | 5,594 | |
| Individuals | 1,923 | | 1,923 | | 1,923 | |

*Statistically significant coefficient at the $p = .01$ level.

stated preference dummy variable), $i = 1, \ldots, 1{,}923$ participants and $t = 1, \ldots, T_i$ time periods. Three participation thresholds are estimated: "definitely yes," "probably yes," and "not sure."

We report regression results in Table 2. We find that the coefficient on the registration fee is negative and statistically significant in each model in accordance with economic theory. In the model where we code only "definitely yes" stated preference responses as participating in BSG, the stated preference dummy variable is negative and statistically significant indicating that the stated preference data understate actual behavior. In the model where we code "definitely yes" and "probably yes" responses as participating, the stated preference variable is not statistically different from zero indicating that the stated preference data is consistent with actual behavior. In the final model, where we code "definitely yes," "probably yes," and "not sure" responses as participating in BSG, the stated preference variable is positive and statistically significant. In this final model, our results indicate that the stated preference data overstate actual behavior and common hypothetical bias result exists. We find that using an intensity of preference correction can mitigate for hypothetical bias but using only individuals who are "definitely sure" will overcorrect the problem.

## VI. APPLICATION

In order to illustrate the potential usefulness of stated preference data, as in the study by Teasley, Bergstrom, and Cordell (1994), we conduct a simulation exercise to determine the revenue maximizing registration fee. Considering the model where "definitely yes" and "probably yes" responses are coded as participating in the event, the average marginal effect of the registration fee coefficient, $\partial\pi/\partial\text{fee} = \Phi(\cdot)\beta_{\text{fee}}$, suggests that a \$10 increase in the registration fee reduces the probability of participation by 2.3% at the mean probability (Table 2). The registration demand is elastic, $\varepsilon_{\text{fee}} = (\partial\pi/\partial\text{fee})(\text{fee}/\pi)$, indicating that an increase in the registration fee would decrease revenue (and vice versa) (Table 2).

A simulation of the probit probability function is used to estimate the number of riders at registration fees between \$0 ($n = 3{,}953$) and \$100 ($n = 90$). Without the quantity constraint of 1,250 riders, fee revenue is maximized at \$160,217 with a fee of \$50 and 3,204 riders. These results could be used by BSG organizers to encourage the National Park Service to relax the quantity constraint. With the quantity constraint, fee revenue is maximized at \$91,250 and a fee of \$72. Preliminary results similar to this were used by BSG organizers to raise the registration fee from \$60 to \$70. Revenue increased by over \$10,000 as a result.

## VII. CONCLUSIONS

Hypothetical bias is considered a major problem in stated preference methods. While the percentage of correct predictions is only around 50%, we find evidence that (1) aggregate predictions based on the actual price increase are more accurate than predictions made with higher and lower prices and (2) the stated preference data accurately predict actual behavior in an empirical model that accounts for unobserved heterogeneity across respondents. Considering (2), we show that respondent certainty corrections can align stated preferences with revealed preferences.

We find that respondents who answer "probably yes" and "definitely yes" about participation in a sports tourism event behave similarly in the actual situation.

Our results are consistent with much of the literature in marketing, environmental, and health economics where researchers are cautiously optimistic about the ability of stated preference data to predict actual behavior (Blumenschein et al. 2008; Champ and Bishop 2001; Sun and Morwitz 2010). In contrast to previous studies, our calibration approach suggests a cutoff that allows for respondent uncertainty compared with other contingent valuation studies that find more certain thresholds best predict actual behavior. We suggest that respondent uncertainty might reflect not only the willingness-to-pay but also the ability to participate based upon the cyclists' physical health and training. Future research should focus on methods that enhance understanding of certainty adjustments in different contexts.

While some may interpret these results as informative, they are not necessarily unbiased estimates of BSG demand. Carson and Groves (2007) argue that the incentive structure of stated preference questions can be used to predict strategic behavior. Because the BSG fee was $60 in 2011 and the rationale for a higher fee was an increase in charitable donations and not a take it or leave it offer, respondents have an incentive to state that they will not participate in an effort to keep the registration fee low. Others may wish to increase charitable donations. Some evidence on the dominance of these types of strategic behavior is from the asymmetric individual prediction errors. Although 29% stated that they definitely would not participate but did, 19% stated that they definitely would participate and did not. Therefore, decision makers should use these results with the caution that the actual BSG demand is likely to be less elastic than the elasticity estimates provided here. The practical implication is that the model might overpredict the changes resulting from higher and lower registration fees. But, at least an educated guess about the direction of the bias can be made. Future research should develop incentive compatible stated preference questions for this context.

Last, we conduct a simulation exercise to provide evidence about whether the stated preference data provide "a practical alternative when prices aren't available" as Carson (2012) claims or is "hopeless" as Hausman (2012) claims. Our interpretation of the data and "real world" experience supports Carson's claim. As a result of the 2011 BSG survey and preliminary analysis of the stated preference data, BSG organizers raised the registration fee to $70 and generated over $10,000 more for charity. This may be prima facie evidence that stated preference data are not "hopeless."

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## SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article:

**Appendix S1.** Willingness-to-pay question (100-mile ride version)