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Abstract

The purposes of this study are to examine the effect of training satisfaction and weather on the intention to revisit a sport event and to assign a monetary value to these event attributes considering attribute non-attendance. It uses survey data from four sport events in the United States in 2017 and 2018. Respondents answered a series of hypothetical scenarios that randomly assign travel costs per mile and travel distances for the return visit along with weather forecasts and training satisfaction. Logit models estimated with and without attribute non-attendance reveal the extent of preference heterogeneity and respondent attention to trip attributes. The monetary value of training satisfaction and favorable weather is obtained by converting willingness-to-travel into willingness-to-pay estimates based on travel costs. The results indicate that attribute non-attendance is an issue in each data set and that willingness-to-pay for event attributes differs across event and time.

Keywords: Intention to revisit; Monetary valuation; Sport event; Willingness-to-pay; Willingness-to-travel

Introduction

The last decades have seen an increase in the number of participatory sport events in endurance sports, such as bike races, marathons, and triathlons, which was associated with an increase in the number of people participating in those events (e.g. Lamont, Kennelly, & Wilson, 2012; Wicker, Hallmann, & Zhang, 2012). These events are classified as recurring sport events, meaning that they are held on an annual basis which gives participants a chance to participate in several editions of the same event (Kaplanidou & Gibson, 2010). In the last years, hosting communities have realized the potential benefits of such recurring sport events with respect to the economic impact caused by visitor spending (Daniels & Norman, 2013) and the positive contribution to the image of the destination (Kaplanidou & Vogt, 2007), suggesting that knowledge about the factors affecting participants' intention to revisit the event is important to both event organizers and local tourism agencies.

Individuals participate for a variety of reasons in such endurance events, including mastery avoidance (Stoeber, Uphill, & Hotham, 2009) and performance against specific reference points (Allen, Dechow, Pope, & Wu, 2016). For example, participants compare their finishing times against their own results from previous editions, with other competitors of their age group, and against specific performance thresholds, such as running a marathon under three or four hours (Allen et al., 2016; Stoeber et al., 2009). The outcome of these comparisons affects individuals' satisfaction with their performance (Stoeber et al., 2009) which, in turn, has a significant positive effect on individuals' general happiness not only directly after the race, but also several weeks after the event (Maxcy, Wicker, & Prinz, 2019). Moreover, satisfaction with the race was found to positively affect the intention to revisit the event and the destination (Wicker et al., 2012).

Given the physical and mental demands of such a competition, participation in such an event requires intensive training and preparation (Lamont et al., 2012; Maxcy et al., 2019). Typically, participants train for several months in an effort to be prepared to deal with the challenges such an endurance event offers (Kennelly, Moyle, & Lamont, 2013; Maxcy et al., 2019). Intuitively, satisfaction with training will be associated with race performance and satisfaction with race outcome. Moreover, weather might also affect the outcome of such a race. As day-of-the-event participation can vary with the weather forecast, event organizers need participation estimates when there is less than ideal weather in the forecast. Consequently, training satisfaction and weather conditions will affect individuals' intention to participate in the event, but these factors were neglected in previous scenarios about the intention to revisit an event (Whitehead, Weddell, & Groothuis, 2016; Whitehead & Wicker, 2018; 2019).

Therefore, the article has two main purposes. The first purpose is to examine the effect of training satisfaction and weather on the intention to revisit the event by considering attribute non-attendance (ANA). ANA arises in stated preference surveys when respondents ignore choice attributes for a variety of reasons (Alemu, Hussen, Mørkbak, Olsen, & Lynge, 2013; Hensher, Rose, & Greene, 2005), yielding biased estimation results. The second purpose is to assign a monetary value to these race attributes using willingness-to-travel (WTT) information which is converted into willingness-to-pay (WTP) estimates. The use of survey data from four events allows results to be compared across events and time in an effort to check their robustness. This article contributes to existing monetary valuation research in the context of sport events by considering multiple attributes in the hypothetical scenario and ANA in the empirical analysis. Another contribution is the comparison across event and time and the estimation of monetary values not only for event participation as a whole, but also for specific event attributes.

Conceptual framework and literature review

Intention to revisit and associated factors

From a conceptual perspective, the intention to revisit an event reflects an individual's stated preferences and behavioral intentions. Following the theory of planned behavior (Ajzen, 1991), behavioral intentions are correlated with actual behavior (i.e. revealed preferences), with stronger intentions resulting in a greater likelihood of displaying the respective behavior. This theory was frequently applied to explain intention to revisit at events and destinations (e.g. Meng & Cui, 2020: Petrick, Morais, & Norman, 2001; Whitehead & Wicker, 2018). Given the interest of tourism destinations and event organizers in knowing about consumers' intention to revisit the destination and/or the event, the factors affecting individuals' intention to revisit have been widely studied – as summarized below.

On the one hand, various factors were found to be positively associated with intention to revisit, including past behavior (Kaplanidou & Gibson, 2010; Petrick et al., 2001), perceived value (Kim, Holland, & Han, 2013; Petrick et al., 2001), satisfaction with the event and/or destination (Eusebio & Vieira, 2013; Kim et al., 2013; Petrick et al., 2001; Sharma & Nayak, 2018), perceived image of the destination and/or the event (Assaker & Hallak, 2013; Phillips, Wolfe, Hodur, & Leistritz, 2013; Wicker et al., 2012), perceived image fit between destination and event (Hallmann & Breuer, 2010), evaluation of destination attributes (Eusebio & Vieira, 2013; Kaplanidou, Jordan, Funk, & Ridinger, 2012), destination atmosphere (Kaplanidou et al., 2012), nostalgia (Cho, Joo, Moore, & Norman, 2019), memorability (Meng & Cui, 2020), service quality (Kim et al., 2013), satisfaction with event participation (Kaplanidou & Gibson, 2010; Wicker et al., 2012), and attitudes towards event participation (Kaplanidou & Gibson, 2010). On the other hand, a negative association was documented for novelty seeking behavior

(George & George, 2004) and travel costs (Whitehead & Wicker, 2018; 2019). The role of weather conditions and training satisfaction was neglected in previous studies.

Monetary valuation based on willingness-to-travel

Existing research has not only identified relevant factors of intention to revisit, it has also assigned a monetary value to event participation (e.g. Whitehead et al., 2016; Whitehead & Wicker, 2018). These valuation studied were based on a hypothetical scenario asking respondents if they would return to an event or a destination under specific hypothetical conditions. Typically, these studies have applied the contingent valuation method (CVM) and asked for respondents' WTP for the scenario to occur or to be avoided (e.g. Whitehead et al., 2016). However, asking for WTP and anything monetary makes respondents price sensitive and might yield protest answers (Heyes & Heyes, 1999).

To address this issue, previous research has suggested applying the contingent behavior method (CBM) which asks for changes in intended behavior contingent on a hypothetical scenario. One potential change in behavior is the additional distance people would be prepared to travel to reach the event under specific conditions (Bakhtiari, Jacobsen, & Jensen, 2014). Hence, asking for an individual's WTT, the maximum distance people would be willing to travel contingent on hypothetical circumstances, makes respondents less price sensitive (Whitehead & Wicker, 2018). WTT answers can be converted into WTP estimates using information about travel costs (Bakhtiari et al., 2014).

Even though the assessment of WTT may reduce respondents' price sensitivity, such a stated preference approach can still be associated with other biases. Previous research has discussed several issues that could bias results of stated preference questions, including strategic, bias, scope issues, and warm-glow effect (Orlowski & Wicker, 2019). The most prominent concern is hypothetical bias, meaning that respondents overstate their WTP (or WTT) because of the hypothetical nature of the question. In such a case, stated preferences (behavioral intentions) are not in line with revealed preferences (actual behavior).

Attribute non-attendance

ANA means that respondents ignore specific attributes for making their choices or for indicating their behavioral intentions in a hypothetical setting (Carlsson, Kataria, & Lampi, 2010; Nguyen, Robinson, Whitty, Kanekod, & Chinh, 2015). Hence, it can be considered another form of hypothetical bias (Koetse, 2017). Respondents do not attend to attributes for several reasons (Nguyen et al., 2015), including the adoption of simplifying strategies (Carlsson et al., 2010), perceived irrelevance of specific attributes (Hensher, Rose, & Greene, 2012), or protest-like behavior (Alemu et al., 2013; Carlsson et al., 2010).

ANA is problematic for the empirical analysis because it yields biased results. Specifically, ANA tends to bias attribute coefficients downwards (in absolute value). Therefore, scholars have suggested two ways how ANA can be addressed (Nguyen et al., 2015). The first option is self-reporting, meaning that respondents are asked to state which attributes they considered in their answers (Carlsson et al., 2010; Hensher et al., 2012). However, this option is problematic as respondents were found to assign the attribute in question only a lower weight rather than a utility of zero (Carlsson et al., 2010).

The second approach is not based on self-reports because it infers ANA from the data through statistical analysis and is, therefore, called inferred ANA (Nguyen et al., 2015; Scarpa, Gilbride, Campbell, & Hensher, 2009). Typically, some form of latent class modelling is applied to identify the extent of ANA (Hensher et al., 2012; Nguyen et al., 2015). One prominent type of inferred ANA uses the latent class logit model and imposes attribute coefficient constraints to identify the probability that a survey respondent will ignore attributes (Scarpa et al., 2009; Scarpa, Zanoli, Bruschi, & Naspetti, 2012). The present study applies this approach.

Methods

Description of sport events and data collection

New River Marathon (NRM). The NRM event includes a marathon, a half marathon, a 5K and a 1 mile fun run.[1] The start and finish is along the New River in Boone, North Carolina (NC), one of only 14 American Heritage Rivers in the United States. The 2017 New River Marathon was held on May 6. The high temperature was 47 degrees and there was 0.02" of rain. Altogether, 147 participants finished the race (94 male, 53 female). Following the 2017 event, an online survey was administered to all 515 runners who had registered for the 2017 edition using Survey Monkey©. After the initial email invitation was sent on May 20 and a reminder on May 27, 172 responses were received and 147 runners completed the survey, yielding a completed response rate of 29%.

Beech Mountain Metric (BMM). The BMM is a classic mountain metric century that begins in Banner Elk, NC and finishes at the top of Beech Mountain in NC. The 2017 BMM, held on May 20, has 8000 feet of climbing. There is also a 43 mile ride with 5600 feet of climbing. The high temperature was 79 degrees with 0.01" of rain. Altogether, 372 people participated in the ride and 244 finished it. Following the 2017 ride on May 20, an online survey was administered to BMM participants using Survey Monkey©. Email invitations were sent to all 325 riders who had registered for the 2017 BMM. After the initial email invitation was sent on June 1st and a reminder on June 8th, 118 responses were received and 116 riders completed the survey. The completed response rate was 36%.

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[1] According to findmymarathon.com, the New River Marathon was the 314th largest marathon in 2017 and 4.8% qualified for the 2017 Boston Marathon.

Blood Sweat and Gears (BSG). BSG is a demanding, long distance road bike ride with a start and finish point in Valle Crucis, NC. The 100 mile route has a cumulative climbing elevation of 8800 feet. There is also a 50 mile ride option with 4200 feet climbing elevation. At the 19th annual BSG, which was held on Saturday June 25, 2017, the high temperature was 68 degrees with no rain. There were 1209 participants, with 862 of them finishing the ride. Following the 2017 ride, an online survey was administered to all 1142 riders who had registered for this edition using Survey Monkey©. After the initial email invitation was sent on July 5 and two reminders on July 14 and July 24, 399 responses were received and 375 riders completed the survey, yielding a completed response rate of 33%.

The 20th annual BSG was held on Saturday June 23, 2018. The high temperature was 78 degrees with 0.01” rain. Altogether, 1190 riders participated in the race and 910 finished it. Following the 2018 ride, an online survey was sent to all 1,125 riders who had registered for the 2018 BSG via email. After the initial email invitation was sent on June 25 and a reminder on July 2, 468 responses were received and 447 riders completed the survey. The completed response rate was 40%.

Hypothetical scenario and attributes

The hypothetical scenario (Fig. 1) considers changes in multiple attributes (i.e. cost per mile, training, weather) and is similar to Söderberg (2014) suggesting a multi-attribute return visitation model for a running race. It extends previous WTT research (Whitehead & Wicker, 2018; 2019) that estimated the WTT return visitation models with data from only one event (BSG) relying on a single question with a single attribute (i.e. additional distance). In each of the current four surveys, respondents were asked to “… please consider some hypothetical situations. We would like to know how likely it is that you would participate in [the event next year] with differences in the costs of travel, your training and the weather conditions." The change in the cost attribute was proposed as the variation in the cost per mile due to changes in fuel costs, maintenance and repair, and tires, while respondent relocation represented the proposed scenario for the additional distance. Satisfaction with training was captured with several training features, including long rides, short high-intensity rides, rest and recovery, and nutrition. The context for the temperature forecast was the typical high temperatures during the month of the event, while the precipitation context ranged from 0% to 100%.

Insert Figure 1 here

Table 1 presents the attribute levels. One of two cost per mile estimates was presented in the 2017 surveys: 12 and 17 cents. In the 2018 survey, 22 cents per mile were added. The additional distance took one of four values: 30, 60, 90, or 120 miles. Satisfaction with training was measured on a 4-point Likert scale ranging from *very satisfied* to *very dissatisfied*. The chance of precipitation took one of seven values: 0% chance, 40%, 60%, or 80% chance of light rain; or 40%, 60%, or 80% chance of heavy rain. For the NRM and BMM events, which take place in May, one of five high temperatures was assigned: 47, 55, 63, 71, or 79 °F. For the BSG taking place in June one of five high temperatures was provided: 70, 74, 78, 82, or 86 °F.

Figure 2 gives an example of a choice question. In the NRM and BMM surveys, respondents were asked: In this new situation, how likely is it that you would participate in the [year] [event]? The response categories were *very likely*, *somewhat likely, neither likely nor unlikely, somewhat not likely,* and *very unlikely*. In the BSG surveys, respondents were then asked: In this new situation, would you plan to participate in the [year] [event]? The five response categories ranged from *definitely yes* to *definitely no*. The choice question was repeated four times in each survey. Each of the attributes was randomly assigned in each question.

Insert Figure 2 here

The estimation sample size was limited to those who drove one-way less than 360 miles, approximately a 6-hour drive. Due to the popularity of BSG, a number of riders travel long distances to participate. In the 2018 sample, 12% travelled more than 360 miles, with an average of 634 miles and a 2100 mile maximum. These riders tend to be insensitive to relatively small changes in travel cost and their inclusion would bias the coefficients of those riders who are sensitive to travel cost. For those riders traveling 360 miles or less, the mean one-way miles driven are as follows: 102 for the NRM (*n*=111), 144 for the BMM (*n*=101), 133 for the 2017 BSG (*n*=313), and 135 for the 2018 BSG (*n*=383).

Table 2 shows the probability of a return visit in the baseline question (without introduction and variation in the attributes) and the probabilities after introduction of the attributes. The return visitation probabilities are lowest with 68% for the NRM and highest for the BMM with 94%[2]. The baseline return visitation probability for BSG is 88% in the 2017 survey and 84% in the 2018 survey. Return visitation declines with the potential for travel cost increases, a chance of rain, and dissatisfaction with training. The mean of the return visitation probabilities over the four scenarios is 40% and 47% for NRM and BMM, respectively, as well as 55% and 57% for BSG in 2017 and 2018, respectively.

Insert Table 2 here

Empirical model

According to random utility theory (Louviere, Flynn, & Carson, 2010; McFadden, 1973), survey respondents will tend to choose whether to visit the event the following year or stay at home depending on which alternative provides the most utility. The individual utility from the

[2] The 2018 BMM was cancelled due to bad weather and discontinued due to declining participation in 2019.

choice is decreasing in cost and increasing in benefit:

$$U_{ij} = V_{ij}(C, T, L, H, S) + e_{ij} \qquad (1)$$

where *U* is the individual indirect utility function; *V* the non-stochastic portion of utility; *C* the travel cost; *T* the temperature forecast; *L* the light rain forecast; *H* the heavy rain forecast; *S* satisfaction with training prior to the event; *e* the error term; $i = 1, \dots, n$ represent the individuals; and $j = 1, 2$ the alternatives (participate or do not participate). The travel cost is equal to the product of the cost per mile and the total miles driven: $C = tc \times 2 \times (m + \Delta m)$, where *tc* is the travel cost per mile, *m* is the status quo one-way miles driven to the event, and Δm is the additional miles that would be driven. The model is estimated as a utility difference, meaning that variables which do not change across the alternatives drop out of the calculation.

The random utility model assumes that the individual chooses the alternative that gives the highest utility, $\pi_{ij} = \Pr(V_{ij} + e_{ij} > V_{ik} + e_{ik}; j \neq k)$, where π_{ij} is the probability that individual i chooses alternative *j*. In line with previous research (Whitehead et al., 2016; Whitehead & Wicker, 2018), the dependent variable is the probability of return visitation. It is equal to one if the respondent answered *very likely* or *somewhat likely* in the NRM and BMM surveys and *definitely yes* or *probably yes* in the BSG surveys, respectively.

If the error terms are independent and identically distributed, and extreme value variates, the multinomial logit (MNL) model should be preferred. Therefore, we estimate MNL models with NLogit version 6 software (www.limdep.com). We first estimate the conditional logit model with the linear utility function $U = \beta_C C + \beta_T T + \beta_L L + \beta_H H + \beta_S S$, where $U_{ijt} = \beta' x_{jit} + e_{ijt}$ and $t = 1, \dots, 4$ choice occasions:

$$Prob(y_{ijt} = 1) = \frac{\exp(\beta' x_{jit})}{\sum_{j=1}^{2} \exp(\beta' x_{jit})} \qquad (2)$$

In three out of four models, the conditional logit (with clustered standard errors) produces a statistically insignificant coefficient on the travel cost variable (these results are provided in the Appendix; Table A1). We then estimate an ECLC inferred ANA model initially with two classes (Koetse, 2017):

$$Prob(y_{it} = j|c) = \frac{\exp(\beta_c' x_{jit})}{\sum_{j=1}^{2} \exp(\beta_c' x_{jit})} \quad (3)$$

where β_c is a class specific parameter vector. The first class is the full preservation class and the second imposes ANA on the travel cost attribute by constraining the coefficient to equal zero, $U = [\beta_C = 0]C + \beta_T T + \beta_L L + \beta_H H + \beta_S S$. All other coefficients are constrained to be equal across the two classes. The probabilities that each respondent is in each class are estimated by an iterative goodness of fit process within the maximum likelihood estimation. The mean of the probabilities that the respondent is in the non-attendance class is an estimate of the extent of hypothetical bias on the travel cost attribute. This model is referred to as *partial ANA model*.

Generalizing this model to one with multi-attribute non-attendance yields the *full ANA model*. It can lead to up to 2^k classes, where *k* is the number of attributes (Nguyen et al., 2015). For example, in our model respondents face a return visitation choice with 4 attributes leading to 16 potential classes (Table A2). A 16 class ECLC model can be estimated with NLOGIT, but our experimental design has 5 attributes once light rain and heavy rain are treated as separate attributes (and 6 attributes in the BMM data). We adopt various simplifying assumptions when estimating a variant of the 2^k model. The primary model estimated is one with a full preservation class, single ANA classes, and a full non-attendance class. With four attributes, this leads to a 6 class model (Table A3):

$$Prob(y_{it} = j|c) = \frac{\exp(\beta_c' x_{jit})}{\sum_{j=1}^{6} \exp(\beta_c' x_{jit})} \quad (4)$$

Results and discussion

Table 3 displays two models for the 2017 NRM return visit. Model 1 is the partial ANA model and Model 2 the full ANA model. The ECLC model outperforms the conditional logit model statistically with higher *Pseudo-*R^2 and lower *AIC* statistics. In Model 1, the coefficient on the travel cost variable is negative: As the cost of participating in the marathon rises, the probability of return visitation falls. This effect is in line with previous research (Whitehead & Wicker, 2018; 2019). Overall, there is a 55% chance that the survey respondent will be in the travel cost non-attendance class.

The NRM travel cost coefficient in the conditional logit model is the only one of the four events that is statistically different from zero (Table A1). However, the coefficient in Model 1 is six times larger (in absolute value; Table 3) than the coefficient estimated without ANA (Table A1). This finding suggests that the WTP estimates from the conditional logit will be biased upwards. As the probability of rain on the day of the event increases, the probability of return visitation decreases. The probability of heavy rain has a larger negative impact in the utility function, but the light rain and heavy rain coefficients are not statistically different. The effect of temperature is positive, indicating that a warmer day is preferred. We find no evidence of non-linear temperature effects. Not surprising, if runners expect to be very satisfied with their training prior to the marathon, they are more likely to return to the event.

Model 2 estimated with non-attendance for each attribute produces similar results. The light rain and heavy rain forecast coefficients are equal. The estimate of the probability that the respondent would statistically ignore the attribute is the sum of the single ANA probability class and the full non-attendance probability class (Tables A3 and A4). Non-attendance to the travel cost attribute is 45%, 10 percentage points lower than non-attendance in Model 1. The corresponding values for non-attendance to the temperature, light rain, heavy rain, and satisfaction with training attributes are 47%, 21%, 21%, and 36%, respectively. Collectively, the coefficients in Model 2 are substantively larger (in absolute value) than those in Model 1. Specifically, the travel cost, temperature, light rain, heavy rain, and training satisfaction coefficients are 14%, 131%, 146%, 83%, and 290% larger, respectively. This finding indicates that non-attendance to the attribute biases the coefficient towards zero. This bias will have implications for WTP for the attribute and participation in the event.

Insert Table 3 here

Table 4 reports the partial and full ANA models for the 2017 BMM return visit. Again, the ECLC model outperforms the conditional logit model statistically with higher *Pseudo-*R^2 and lower *AIC* statistics. In Model 1, the coefficient on the travel cost variable is negative and statistically significant and there is a 62% chance that the survey respondent will be in the travel cost non-attendance class. Contrary to the NRM model (Table 3), the coefficients on the rain variables are not statistically different from zero in Model 1.[3] In the conditional logit model (Table A1), these coefficients are negative and statistically different from zero. Again, the effect of temperature is positive and significant and there is no evidence of non-linear temperature effects. Like in the NRM model, participation in the marathon is significantly more likely when riders are expected to be satisfied with their training. The date of the event has no significant effect on return visitation.

In the model with non-attendance estimated for each attribute (Model 2), the results for

[3] The relative lack of an impact of the rain attribute in the BMM models may be related to a coding error that left us unable to determine which attribute the respondent received in the third scenario. We constrain the coefficients on the rain variables to be equal to zero in this scenario and rely on the first, second, and fourth scenarios for estimation of the rain coefficients. Similar results are found when the scenario 3 data are excluded from estimation. Nevertheless, we do not attempt to infer too much from the rain attribute results in the BMM model.

several coefficients are similar with the exception of the light rain coefficient which becomes statistically significant. Non-attendance to the travel cost attribute is 63%, almost equal to that in Model 1. The corresponding values for non-attendance to the temperature, light rain, heavy rain, satisfaction with training, and event date attributes are 65%, 44%, 60%, 44%, and 44%, respectively. The coefficients in Model 2 are substantively larger (in absolute value) than those in Model 1. In particular, the travel cost, temperature, and training satisfaction coefficients are 173%, 494% (6 times) and 217% larger, respectively.

Insert Table 4 here

Table 5 presents the partial and full ANA models for the 2017 BSG. As in the previous two events, the ECLC model outperforms the conditional logit model statistically with higher *Pseudo-R^2* and lower *AIC* statistics. In Model 1, the coefficient on the travel cost variable is negative and statistically significant, with a 64% chance that the survey respondent will be in the travel cost non-attendance class. The high level of non-attendance explains the low *t*-statistic on the travel cost variable in the conditional logit model. Otherwise, the conditional logit model performs well, with coefficient estimates showing expected signs and precision. Similar to the NRM model, as the probability of rain on the day of the event increases, the probability of participation decreases. Similar to the NRM and BMM models, the effect of temperature is positive. However, and in contrast to the previous two events, we find evidence of non-linear temperature effects. Including a temperature squared variable in addition to temperature reveals an inverse u-shaped relationship: The probability of return visitation increases with increasing temperature, but at a decreasing rate. This is likely due to the mid-summer timing of the event. Finally, and similar to the other two events, satisfaction with training has a significant positive effect on the intention to return to the event.

In Model 2, the results for each of the coefficients are qualitatively similar to those in Model 1. The estimates of non-attendance to each attribute are lower than in the other full ANA models. This difference may be due to the higher sample or a different Likert scale for the dependent variable. Non-attendance to the travel cost attribute falls to 34%. Non-attendance to the temperature, light rain, heavy rain, satisfaction with training, and event date attributes is 26%, 15%, 0%, and 9%, respectively. Other than the travel cost coefficient, each of the coefficients in Model 2 are substantively larger (in absolute value) than those in Model 1. In particular, the temperature, light rain, heavy rain, and training satisfaction coefficients are 113%, 199%, 49%, and 47% larger, respectively. In contrast to the other 2017 events, the coefficient on the travel cost parameter falls by 34% from Model 1 to Model 2. This may be due to the lower estimate of the probability of non-attendance to this variable.

Insert Table 5 here

Table 6 displays two ANA models estimated with the BSG 2018 return visitation data. These data support estimation of a variation of the n^k model. We first estimated a model similar to those estimated for the 2017 events (Table A5). Upon finding that light rain was fully attended, we estimated the n^k model with light rain excluded from the k attributes. Since the n^k model also outperforms the model in Table A5, we choose to present this as our best model, even though it is not directly comparable to the 2017 event models. As in all of the previous events, the ECLC model outperforms the conditional logit model statistically with higher *Pseudo-R^2* and lower *AIC* statistics.

Model 1 reveals a 59% chance that the survey respondent will be in the travel cost non-attendance class. The high level of non-attendance explains the low *t*-statistic (1.66) on the travel cost variable in the conditional logit model. Otherwise, the conditional logit model performs well, with coefficients being estimated with expected signs and good precision. Like in two other events, as the probability of rain on the day of the event increases, the probability of participation decreases. Similar to the BSG 2017 result, we find an inverse u-shaped relationship between forecast temperature and return visitation. Again, satisfaction with training increases the likelihood or return to the event.

In Model 2, the results for each of the coefficients are qualitatively similar to those in Model 1. The estimates of non-attendance to each attribute are higher than in the BSG 2017 return visitation model (but the model in Table A5 has similarly low overall attribute non-attendance). Non-attendance to the travel cost attribute is similar to that in Model 1, while non-attendance to the temperature, heavy rain and satisfaction with training is 58%, 37%, 40%, and 52%, respectively. Other than the travel cost coefficient, each of the coefficients in Model 2 is substantively larger (in absolute value) than its counterpart in Model 1. Specifically, the temperature, light rain, heavy rain, and training satisfaction coefficients are 59%, 23%, 114% and 416% larger, respectively. Similar to the BSG 2017 model, the coefficient on the travel cost parameter falls by 33% from Model 1 to Model 2. In the BSG 2017 model, we speculated that this may be due to the lower estimate of the probability of non-attendance to the travel cost variable. Since non-attendance in the two BSG 2018 models is similar, it is not clear why there is a difference in the travel cost coefficients.

Insert Table 6 here

Table 7 summarizes the WTP estimates for all events and attributes. The WTP for a one unit change in the attribute x is equal to the negative of the ratio of the attribute coefficient to the cost coefficient, $WTP_x = -\beta_x/\beta_C$. All but one of the WTP estimates from Model 2 are greater than those in Model 1. The outlier is WTP to avoid heavy rain which is estimated with the wrong sign (and may be due to the coding error in the BMM model). We find that WTP for warmer temperatures is equal in May, but even greater in the warmer month of June. This latter result is estimated with an inferior functional form, so it should be further pursued. WTP to avoid rain is similar across events, but the value of light rain versus heavy rain is not statistically different. Performance is very important to survey respondents, with the value of a return visitation ranging from $27 to $154 when the participants are very satisfied with their training relative to being somewhat satisfied or even worse.

Insert Table 7 here

Conclusion

This study examined the effects of training satisfaction and weather conditions on individuals' intention to revisit the event and to assign a monetary value to these event attributes. It extends existing research (Whitehead & Wicker, 2018; 2019) using data from only one event (Blood Sweat and Gears) and relying on a single question with a single attribute (i.e. additional distance) by including changes in multiple attributes (i.e. cost per mile, distance, training, light rain, heavy rain, and temperature). Another contribution is the consideration of ANA in the empirical analysis: Econometrically, we estimated a set of conditional logit models and compared them to inferred partial (travel cost only) and full ANA ECLC models considering ANA for all attributes.

For all four events, the models accounting for ANA outperform standard models, indicating that the application of the ANA models is robust to changes in event and time. Moreover, ANA was found to be present in each attribute across event and time. All coefficients are larger when ANA is accounted for except the travel cost coefficient in the BSG models. Non-attendance to travel cost is a major issue in the conditional logit models: The extended scenario with multiple attributes rendered the coefficient on the travel cost variable statistically insignificant in three of the four events, suggesting that ANA materially affects the estimations. Accounting for ANA in just the travel cost coefficient effectively deals with this problem. Regarding WTP, neglecting ANA resulted in an inability to estimate statistically significant WTP for attributes in three of the four conditional logit models. In the BSG models, the effect of controlling for ANA unambiguously increases WTP for the attributes. In the other models, the overall effect of accounting for ANA on WTP is ambiguous.

This study has implications for research and practice. Starting with research implications, the findings highlight that the choice of the estimator is important because it materially affects the results. Specifically, the estimates obtained with conditional logit models were qualitatively and quantitatively different from the ECLC logit models. Hence, future studies applying the inferred ANA approach should use the latter estimator. Furthermore, the results reveal that many respondents ignored survey attributes when answering hypothetical scenarios. Although ANA varied across event and attribute, it was considerably high for some attributes. Considering ANA for multiple attributes produces substantially larger (but more appropriate) estimates. This finding is important because it does not only have implications for WTT and WTP studies, but also for studies using other approaches to assess stated preferences such as choice experiments.

Turning to practical implications, the findings suggest that participants' intention to revisit a sport event depends significantly on factors that are beyond the control of event managers and tourism agencies. These are the temperature at the day of the event, the chance of light or heavy rain, and individuals' satisfaction with training prior to the event. Thus, some participants might not show up on the race day not because of poor event organization, but because of other factors that are not controllable by event management. These aspects should be accounted for in event planning. Collectively, the findings reveal that participants who have intentionally registered for a mentally and physically challenging race are quite sensitive to weather conditions. Hence, preparation does not seem to include dealing with poor weather conditions which should, therefore, be integrated into the training phase for the event.

The study's limitations represent avenues for future research. One question we leave unanswered is how to handle WTP estimates that may only be representative of a selected sample; i.e., those who pay attention to the choice exercise. One way to interpret these is that they are representative of the full sample, if the full sample had paid attention. Another interpretation is that these are the WTP estimates for only those who paid attention. Until further research can identify the meaning of ANA, researchers should rely on sensitivity analysis when aggregating WTP estimates. Future research should also explore design techniques that will decrease non-attendance.

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Table 1

Experimental design

<table>
<tr><th>Attribute</th><th>New River Marathon 2017</th><th>Beech Mountain Metric 2017</th><th>Blood Sweat and Gears 2017</th><th>Blood Sweat and Gears 2018</th></tr>
<tr><td>Cost per mile</td><td colspan="3">12, 17 cents per mile</td><td>12, 17, 22 cents per mile</td></tr>
<tr><td>Additional distance</td><td colspan="4">30, 60, 90, 120 miles</td></tr>
<tr><td>Satisfaction with training</td><td colspan="4">Very satisfied, somewhat satisfied, somewhat dissatisfied, very dissatisfied</td></tr>
<tr><td>Precipitation</td><td colspan="4">0% chance, 40%, 60%, 80% chance of light rain,
40%, 60%, 80% chance of heavy rain</td></tr>
<tr><td>Temperature</td><td colspan="2">47, 55, 63, 71, 79 degree high temperature</td><td colspan="2">70, 74, 78, 82, 86 degree high temperature</td></tr>
<tr><td>Event Date</td><td>NA</td><td>Memorial Day weekend or the weekend before</td><td colspan="2">NA</td></tr>
</table>

Table 2

Probabilities of return visitation (in %)

	New River Marathon 2017	Beech Mountain Metric 2017	Blood Sweat and Gears 2017	Blood Sweat and Gears 2018
Baseline	68	94	88	84
Choice 1	40	55	60	68
Choice 2	36	51	55	59
Choice 3	41	39	54	51
Choice 4	41	41	50	52
Sample size	111	109	313	383

Table 3

Equality constrained latent class logit models for the New River Marathon 2017 (dependent variable: probability of a return visit)

	Model 1				Model 2			
	Coeff	SE	t-stat	ANA	Coeff	SE	t-stat	ANA
Travel cost	-0.075***	0.010	-7.69	55%	-0.086***	0.031	-2.76	45%
Temperature	0.028***	0.005	5.22	NA	0.063***	0.021	2.97	47%
Light rain	-0.017***	0.005	-3.14		-0.042**	0.018	-2.36	21%
Heavy rain	-0.023***	0.005	-4.29		-0.042***	0.013	-3.35	21%
Training	0.594*	0.345	1.72		2.320*	1.359	1.71	36%
Pseudo-R^2	0.186				0.209			
AIC	513.1				504.7			
Respondents	111				111			
Time periods	4				4			

Note: *** p<0.01; ** p<0.05; * p<0.10.

Table 4

Equality constrained latent class logit models for the Beech Mountain Metric 2017 (dependent variable: probability of a return visit)

	Model 1				Model 2			
	Coeff	SE	t-stat	ANA	Coeff	SE	t-stat	ANA
Travel cost	-0.042***	0.008	-5.55	62%	-0.10***	0.04	-2.92	65%
Temperature	0.015***	0.004	4.17		0.08***	0.03	2.85	64%
Light rain	0.001	0.005	0.28		0.04*	0.02	1.81	45%
Heavy rain	-0.008**	0.004	-1.99	NA	0.03	0.02	1.61	61%
Training	0.494*	0.281	1.76		1.70*	1.02	1.66	45%
Date	-0.198	0.234	-0.85		-0.76	0.72	-1.06	45%
Pseudo-R^2	0.10				0.22			
AIC	557.6				1676.6			
Respondents	109				109			
Time periods	4				4			

Note: *** p<0.01; **p<0.05; *p<0.10.

Table 5

Equality constrained latent class logit models for Blood Sweat and Gears 2017 (dependent variable: probability of a return visit)

	Model 1				Model 2			
	Coeff	SE	t-stat	ANA	Coeff	SE	t-stat	ANA
Travel cost	-0.058***	0.006	-9.68	64%	-0.038***	0.009	-4.27	34%
Temperature	0.027***	0.003	8.73	NA	0.057***	0.009	6.61	26%
Light rain	-0.017***	0.004	-4.71		-0.050***	0.010	-4.80	15%
Heavy rain	-0.029***	0.004	-8.07		-0.043***	0.006	-7.04	0%
Training	0.933***	0.185	5.03		1.375***	0.262	5.25	9%
Pseudo-R^2	0.17				0.207			
AIC	1452.9				1394.6			
Respondents	313				313			
Time periods	4				4			

Note: *** p<0.01; ** p<0.05; * p<0.10.

Table 6

Equality constrained latent class logit models for Blood Sweat and Gears 2018 (dependent variable: probability of a return visit)

	Model 1				Model 2 (2^k model)			
	Coeff	SE	t-stat	ANA	Coeff	SE	t-stat	ANA
Travel cost	-0.049***	0.0031	-15.7	59%	-0.032***	0.008	-4.02	58%
Temperature	0.029***	0.0030	9.66	NA	0.046***	0.005	8.61	37%
Light rain	-0.013***	0.0032	-4.17		-0.017***	0.004	-4.06	40%
Heavy rain	-0.025***	0.0034	-7.58		-0.055***	0.008	-6.70	
Training	0.969***	0.182	5.33		5.000***	1.066	4.69	52%
Pseudo-R^2	0.186				0.235			
AIC	1587.4				1665			
Respondents	383				383			
Time periods	4				4			

Note: *** p<0.01; ** p<0.05; * p<0.10.

Table 7

Overview of WTP estimates

	New River Marathon 2017					
	Model 1			Model 2		
	WTP	SE	t-stat	WTP	SE	t-stat
Temperature	0.37***	0.07	5.45	0.74***	0.20	3.69
Light rain	-0.23***	0.07	-3.17	-0.50***	0.16	-3.04
Heavy rain	-0.31***	0.07	-4.39	-0.49***	0.15	-3.29
Training	7.93*	4.64	1.71	27.12**	12.88	2.11
	Beech Mountain Metric 2017					
	Model 1			Model 2		
	WTP	SE	t-stat	WTP	SE	t-stat
Temperature	0.34***	0.10	3.30	0.74***	0.09	8.26
Light rain	0.06	0.12	0.50	0.42***	0.13	3.11
Heavy rain	-0.14	0.11	-1.28	0.25*	0.13	1.87
Training	14.01*	7.40	1.89	16.30**	7.43	2.19
	Blood Sweat and Gears 2017					
	Model 1			Model 2		
	WTP	SE	t-stat	WTP	SE	t-stat
Temperature	0.47***	0.07	6.28	1.24***	0.18	6.97
Light rain	-0.29***	0.06	-4.52	-0.69***	0.20	-3.51
Heavy rain	-0.50***	0.07	-6.82	-1.00***	0.15	-6.58
Training	16.16***	3.38	4.78	42.07***	13.40	3.14
	Blood Sweat and Gears 2018					
	Model 1			Model 2		
	WTP	SE	t-stat	WTP	SE	t-stat
Temperature	0.60***	0.07	9.12	1.42***	0.37	3.88
Light rain	-0.28***	0.07	-4.19	-0.51***	0.17	-3.03
Heavy rain	-0.52***	0.07	-7.52	-1.68***	0.44	-3.79
Training	19.97***	3.71	5.38	154.06***	33.73	4.57

Note: *** p<0.01; **p<0.05; *p<0.10.

Figure 1. *Attribute context for the 2017 surveys.*

As you are answering these questions please consider that:

- Each year, the AAA estimates the costs to operate a vehicle in the United States. Operating costs include fuel, maintenance and repair, and tires. Between 2008 and 2016, the AAA estimated that the operating cost for an average sedan has ranged from 12 to 17 cents per mile. The operating cost for sport utility vehicles, trucks and minivans is typically between 2 and 7 cents per mile higher.
- On any given day, thousands of people are moving to a new home all over the country. There are many reasons why people move. Some are to do with finances and career changes, others with personal relationships and changes to the family unit.
- Training involves long rides, short high intensity rides, rest and recovery and nutrition. You may be very satisfied, somewhat satisfied, somewhat dissatisfied or very dissatisfied with your training.
    - NRM: Training involves base mileage, long runs, speed work, rest and recovery and nutrition. You may be very satisfied, somewhat satisfied, somewhat dissatisfied or very dissatisfied with your training.
- The high temperature in late June in Valle Crucis has ranged from 70 degrees to 86 degrees. The chance of rain can range from 0% to 100%.
    - NRM: The high temperature in early May in Boone has ranged from 47 degrees to 79 degrees. The chance of rain can range from 0% to 100%.

Note: NRM is the New River Marathon event version.

Figure 2. *An example for a choice question*.

Please consider the following situation.
Suppose that in 2018 the operating costs for an average sedan are **12** cents per mile.
Suppose that for some reason you move **90** miles farther away from Blood Sweat and Gears.
Suppose that you are somewhat satisfied with your training before Blood Sweat and Gears.
Suppose the weather forecast includes a **78** degree high temperature.
Suppose the weather forecast includes a **40% chance of light rain**.
In this new situation, would you plan to participate in the 2018 Blood Sweat and Gears?

- Definitely yes
- Probably yes
- Not sure
- Probably no
- Definitely no

Note: The bold text is randomly assigned.

Appendix

Table A1

Conditional logit models (with clustered standard errors)

	New River Marathon 2017			Beech Mountain Metric 2017		
	Coeff	SE	t-stat	Coeff	SE	t-stat
Travel cost	-0.012**	0.005	-2.45	-0.001	0.003	-0.41
Temperature	0.009**	0.004	2.04	0.008***	0.003	3.00
Light rain	-0.008*	0.004	-1.95	-0.006*	0.004	-1.66
Heavy rain	-0.011***	0.004	-2.85	-0.011**	0.004	-2.61
Training	0.221	0.211	1.05	0.315	0.209	1.51
Date				-0.237	0.205	-1.16
Pseudo-R2	0.0346			0.0272		
AIC	587.7			598.2		
Respondents	111			109		
Time periods	4			4		
	Blood Sweat and Gears 2017			Blood Sweat and Gears 2018		
	Coeff	SE	t-stat	Coeff	SE	t-stat
Travel cost	-0.0028	0.003	-0.89	-0.003	0.002	-1.66
Temperature	0.013***	0.003	4.21	0.012***	0.003	4.73
Light rain	-0.011***	0.003	-4.21	-0.006***	0.002	-2.62
Heavy rain	-0.021***	0.003	-7.44	-0.016***	0.002	-6.50
Training	0.66***	0.15	4.42	0.556***	0.137	4.07
Pseudo-R2	0.0545			0.0382		
AIC	1639.8			2020.5		
Respondents	313			383		
Time periods	4			4		

Note: *** p<0.01; **p<0.05; *p<0.10.

Table A2

The 2^k latent class model with $k = 4$ estimated with the 2018 BSG data (light rain was not included due to its full attendance)

Class	Description	Utility Function	Class Probability
1	Full Preservation	$U = \beta_C C + \beta_T T + \beta_H H + \beta_S S$	7%
2	One attribute non-attendance	$U = \beta_C C + \beta_T T + \beta_H H + 0S$	14%
3		$U = \beta_C C + \beta_T T + 0H + \beta_S S$	0%
4		$U = \beta_C C + 0T + \beta_H H + \beta_S S$	7%
5		$U = 0C + \beta_T T + +\beta_H H + \beta_S S$	3%
6	Two attribute non-attendance	$U = \beta_C C + \beta_T T + 0H + \beta_S S$	0%
7		$U = \beta_C C + 0T + +\beta_H H + 0S$	9%
8		$U = 0C + \beta_T T + +\beta_H H + 0S$	11%
9		$U = \beta_C C + 0T + 0H + \beta_S S$	0%
10		$U = 0C + \beta_T T + 0H + \beta_S S$	24%
11		$U = 0C + 0T + \beta_H H + \beta_S S$	7%
12	Three attribute non-attendance	$U = \beta_C C + 0T + 0H + 0S$	5%
13		$U = 0C + \beta_T T + 0H + 0S$	5%
14		$U = 0C + 0T + \beta_P H + 0S$	1%
15		$U = 0C + 0T + 0H + \beta_S S$	0%
16	Full Non-attendance	$U = 0C + 0T + 0H + 0S$	7%

Table A3

Full preservation, one attribute, and full non-attendance model

Class	Description	Utility Function
1	Full Preservation	$U = \beta_C C + \beta_T T + \beta_L L + \beta_H H + \beta_S S$
2		$U = 0C + \beta_T T + \beta_L L + \beta_H H + \beta_S S$
3		$U = \beta_C C + 0T + \beta_L L + \beta_H H + \beta_S S$
4	One attribute non-attendance	$U = \beta_C C + \beta_T T + 0L + \beta_H H + \beta_S S$
5		$U = \beta_C C + \beta_T T + \beta_L L + 0H + \beta_S S$
6		$U = \beta_C C + \beta_T T + \beta_L L + \beta_H H + 0S$
7	Full non-attendance	$U = 0C + 0T + 0L + 0H + 0S$

Table A4

Full preservation, one attribute, and full non-attendance model: Class probabilities for four models

Class	Description	NRM	BMM	BSG 2017	BSG 2018
1	Full Preservation	14%	0%	16%	0%
2		24%	19%	34%	26%
3		26%	21%	26%	46%
4	One attribute non-attendance	0%	0%	15%	0%
5		0%	16%	0%	9%
6		15%	0%	9%	19%
6	Full non-attendance	21%	44%	0%	NA

Table A5

Full preservation, one attribute, and full non-attendance model

	Blood Sweat and Gears 2018		
	Coeff	SE	t-stat
Travel cost	-0.010***	0.003	-3.84
Temperature	0.043***	0.005	9.01
Light rain	-0.014***	0.003	-4.22
Heavy rain	-0.032***	0.004	-7.55
Training	1.387***	0.234	5.92
Pseudo-R2	0.220		
AIC	1676.6		
Respondents	383		
Time periods	4		
	WTP		
	Coeff	SE	t-stat
Temperature	4.41***	1.31	3.38
Light rain	-1.39**	0.57	-2.45
Heavy rain	-3.27***	1.04	-3.15
Training	140.85***	34.04	4.14

Note: *** p<0.01; ** p<0.05; * p<0.10.