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Introduction

The economic impact of sporting mega-events is a well-studied topic in sports economics. For instance, Robert Baade and coauthors have studied the economic impact of the world cup (Baade and Matheson, 2004), the summer Olympics (Baade and Matheson, 2002), the winter Olympics (Baade, Baumann, and Matheson, 2010), the major league all-star game (Baade and Matheson, 2001), the Superbowl (Matheson and Baade, 2006), and the Daytona 500 (Baade and Matheson, 1990). The results of all these studies are that the economic impact rarely, if ever, justifies the public spending on the megaevents particularly if there are many firms bidding to host the event.

One area that is understudied is the economic benefits of local sports participation in events or micro-events. In a recent study Andreff (2022) explicitly states that the "economics of competitive amateur sport" and "sport participation" are under-researched areas. Our study focuses on a local participatory bike race called the "Beech Mountain Metric" (BMM), an amateur road bicycle event. We measure both the economic impact of the event on the local economy and the consumer surplus benefits to participants using stated preference methods. Whitehead and Wicker (2018) estimate the consumer surplus of a trip to participate in the "Blood Sweat and Gears" road bicycle ride with willingness to travel questions, in this study we also use the willingness to travel technique.

One problem with the stated preference data is that it might suffer from hypothetical bias where respondents state they will participate in the event in the future and then fail to attend leading to a difference between stated preferences and revealed preferences. Whitehead, Groothuis, and Weddell (2012) find some evidence the stated preference data with a registration fee increase accurately predicts actual behavior with the price increase. Additionally, Whitehead and Wicker (2019) argue that combining revealed and stated preference data can be used to mitigate hypothetical bias in stated preference data. Using jointly estimated revealed and stated preference data models, a mitigation approach is to include a dummy variable for the stated preference scenarios to control for hypothetical bias. In this chapter we attempt to replicate the Whitehead and Wicker (2019) results with data from three years of a similar, but smaller, road bicycle ride.

Data

Our data is from the amateur road bicycling event BMM. The BMM was a 100-kilometer ride that starts in Banner Elk, NC finishes at the top of Beech Mountain, and includes 8000 feet of climbing. In addition to the 100 km ride, there was also a shorter ride with 5600 feet of climbing. The first BMM was held on Saturday, May 17, 2014. The BMM was discontinued following the cancellation of the 2018 ride.

Following the 2014, 2015, 2016, and 2017 rides an online survey was administered to registered BMM participants. Email invitations were sent to 728 riders who had registered for the 2014 BMM. After the initial email invitation was sent on May 20 and a reminder on May 27, 310 responses were received and 297 riders completed the online survey. The completed response rate was 41%. Email invitations were sent to 655 riders who had registered for the 2015

BMM. After the initial email invitation was sent on May 21 and two reminders, 274 responses were received and 266 riders completed the survey. The completed response rate was 41%. In 2016, email invitations were sent to 420 registered riders. After the initial email invitation on June 3 and a reminder on June 8, 132 responses were received and 130 riders completed the survey. The completed response rate was 31%. We conducted a survey following the 2017 ride which was used in Whitehead and Wicker (2020). The 2018 BMM was cancelled due to bad weather and then the BMM was discontinued due to declining participation. We use the data from the first three years of the BMM in this chapter to develop economic impact and willingness to travel analyses.

Economic Impact

Methods

Economic impact analysis considers the effect of an economic event on a defined local economy. Economic impacts are measured in terms of expenditures (i.e., income) and jobs generated in the local economy as a result of an event. Economic impacts include direct, indirect, and induced spending. Direct spending is the amount of money spent as reported by survey respondents. Indirect spending is the amount of money that is estimated to be spent in the local economy on inputs by industry. Induced spending is the amount of money that is estimated to be spent in the local economy by workers in the industry.

A number of community-based economic impact analyses have been conducted by students from the Appalachian State University Student Chapter of the National Association for Business Economics and faculty in the Department of Economics. These studies have community-based clients who have a demand for research but limited funds to support it. Clients have included the Beech Mountain Metric, Blood Sweat and Gears, and Blue Ridge Brutal road bike rides, and the Blue Ridge Relay and New River Marathon runs. Economic impact estimates range from \$150,000 to \$1,000,000 for these local events.

Data for these community-based projects are obtained from online surveys using email lists of event participants. All the participants with valid email addresses (N) are sent an email message inviting them to complete the online survey. A follow-up email invitation is sent about one week later to those who have not responded. The sample size (n) is equal to the number of completed questionnaires. The response rate is equal to the completed questionnaires divided by the number of participants (n/N).

Respondents are asked if they are residents of the local area and if they traveled away from their home to attend the event. Only non-local visitors inject new spending into a local economy. The non-local visitation rate ($\%v$) is equal to the non-local visitors who traveled to the event (v) divided by the sample size ($\%v = v/n$). These visitors are asked to report the number of days or nights (D) spent in the local area and the number of friends and family members in their travel party (P). Respondents are asked to report the amount of money their travel party spent on their trip in several broad categories: food/supplies (F), lodging (L), travel (T), tourist attractions (A) and other spending (O). The registration or ticket fee revenue (R) is not reported in the survey but is included in the spending total.

The mean value of each spending category is calculated with zero values included for those respondents who did not spend money in that category. The mean value of total spending in each category, $S = [F, L, (T/2), A, O, R]$, is calculated as: $\bar{S} = \sum_{i=1}^{v} S_i / v$, where $i = i, \dots v$

visitors. Transportation spending is divided by two, assuming that one-half is expended outside the local economy.

An injection of spending circulates through the local economy to create indirect and induced spending. Economic impact (EI) per industry per respondent is estimated by multiplying average spending by industry-specific RIMS II multipliers (M) for the High-Country Region (Ashe, Avery, and Watauga Counties): $EI_{ij} = \bar{S} \times M$. RIMS is an acronym for the Regional Input-Output Modeling System, a model developed by the U.S. Bureau of Economic Analysis. Multipliers for the High-Country economic area were purchased by the Department of Economics in 2013. We use Type II multipliers which estimate indirect and induced spending associated with the tourism sector. Economic impact per respondent is summed over the number of non-local visitors to obtain economic impact per industry, $EI = EI_i \times (N \times [v/n])$.

Results

We estimate that in the 2014 BMM race there were 566 participants who traveled from their homes to the area (Table 1). For these participants average total spending was $359 during their stay. Eighty-one percent of the BMM respondents who traveled to the event stayed overnight. The top two categories for expenditures were lodging and food/supplies. Average lodging expenditures were $161 and average food expenditures were $102. Summing total spending over the total number of non-local participants yields total direct spending of $203 thousand associated with the BMM event. Applying a RIMS II multiplier of 1.48 for the tourism sector yields a total economic impact of $301 thousand.

Considering those respondents who participated in the 2015 BMM ride and traveled from their homes to the area (n=506), average total spending was $365 during their stay. Eighty-three percent of the out-of-town respondents stayed overnight. Average lodging expenditures were $187 and average food expenditures were $128. Summing over the total number of non-local participants in 2015 yields total direct spending of $185 thousand associated with the BMM event. Applying a RIMS II multiplier yields a total economic impact of $273 thousand.

Considering those respondents who participated in the 2016 ride and traveled from their homes to the area (n=321), the average total spending was $390 during their stay. Eighty-five percent of the respondents who traveled to the area stayed overnight. Average lodging expenditures were $232 and average food expenditures were $112. Summing spending on all categories over the total number of non-local participants in 2015 yields a total direct spending of $125 thousand associated with the BMM event. Applying a RIMS II multiplier a total economic impact of $185 thousand.

For mega-events, there is always a potential for crowding out of other tourist activities when the mega-event occurs – such as the closing of the theaters during the London Olympics. With a micro-event, however, such as a participatory bike race, we expect that the crowding out effect is minimal particularly because this type of race occurs in two ski resort towns in May, after the winter ski season and before the summer tourist season.

Willingness to Travel

Two return visitation questions are asked in each survey. The first return visit intention question in the 2014 survey was: “Do you plan to participate in the 2015 Beech Mountain Metric?” The second question was: “Suppose that you had to drive further to get to Beech

Mountain Metric in 2015 compared to your driving distance in 2014. For example, you might move further away from Beech Mountain. Would you plan to participate in the 2015 Beech Mountain Metric at the following additional driving distances (one-way)?" Respondents were presented with five different mileages (30, 60, 90, 120, and 150). The potential response options were definitely no, probably no, not sure, probably yes, and definitely yes (see Figure 1).

Similar questions were asked in the 2015 survey and to about 50% of the respondents in the 2016 survey. We call these the "payment card" questions. In the 2016 survey about one-half of the respondents received a "dichotomous choice" question, with each respondent being presented only one randomly selected additional distance (Δd). The question read: "Would you plan to participate in the 2017 Beech Mountain Metric if you had to drive Δd more miles (one-way)?"

In order to compare the payment card and dichotomous choice question versions, we randomly select one of the payment card responses. In Whitehead and Wicker (2019) we include the first stated preference question with the zero additional miles question in the random selection for the payment card version of the data. In this chapter we pursue a strategy that allows for a more efficient comparison between the stated preference and revealed preference data. One response from the five potential additional driving distances was randomly selected from the payment card additional distance questions for the empirical analysis and all of the responses to the first stated preference question in the survey are included.

Whitehead et al. (2016) and Whitehead and Wicker (2018) investigated alternative recodings of the stated preference variable (e.g., definitely yes vs. probably and definitely yes). Following Whitehead et al. (2016), who found that the probably and definitely yes respondents more accurately predicted actual behavior, and Whitehead and Wicker (2018) who found that definitely yes models are less statistically robust, we code the answer as a stated preference return visit if the respondent answered either probably yes or definitely yes.

In Table 2 we present the stated preference and revealed preference registrations for the 2015, 2016, and 2017 BMM rides. The stated preference for return visitation for the 2015 ride year was 83% at the time of the 2014 survey. Only 46% of these riders actually registered for the 2015 year. The pattern is the same for the 2016 and 2017 ride years with over 85% saying that they would probably or definitely ride the following year but about half that actually riding. In contrast, the percentage of respondents who state that they would definitely participate in the following year is slightly lower than the actual participation rate in each year.

Considering the responses to the second stated preference question, as distance traveled increases the return visitation decreases monotonically for each higher distance in years 2015 and 2016. This is not the case in the 2017 BMM ride year data but this is likely due to the smaller overall sample

Empirical Model

The empirical analysis is grounded in utility theory and follows Whitehead and Wicker (2019). Stated preference models for each year of the return visitation measures were estimated with dependent variables in Table 2. Each respondent has three observations for each year in which they answered the survey: the two stated preference observations, status quo distance and increased distance, and the revealed preference observation. These are stacked and we estimate a random parameter logistic regression model:

$$\ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 \Delta TC + \beta_2 Y + \beta_3 SP + \beta_4 (\Delta TC \times DC) + e_t^*$$

where π is the probability of a return visit, ΔTC is the change in travel cost, Y is household income, SP is a dummy variable for the stated preference observations, and DC is a dummy variable for dichotomous choice question format, and e_t^* is a random error term, $t = 1, 2, 3$ (with subscripts for individuals suppressed for simplicity). The random parameters logit allows for preference heterogeneity across individuals. For the fixed coefficient logit model, the parameter vector, β, is assumed to be constant across individuals. To allow for preference heterogeneity, we assume that individual preferences randomly vary according to a population distribution such that $\beta_i = \beta + \sigma_i$, where β is an unknown, but constant parameter for preferences, and σ_i is an individual specific random error component for preferences that are distributed across individuals. The random parameter model is estimated with normally distributed coefficients and 500 Halton draws.

The change in travel cost (ΔTC) was measured as the sum of out-of-pocket travel costs and the opportunity cost of time using the following equation: $\Delta TC = (c \times 2 \times \Delta d) + \big(\gamma \times w \times (2 \times \Delta d/mph)\big)$, where $c = 0.13$ is the operating cost per mile (American Automobile Association, 2015), Δd is the change in one-way distance (in miles), $\gamma = 0.33$ is the fraction of the wage rate, and $w = Y/2000$, Y is household income, and mph is 50 miles per hour – the average driving speed in North Carolina. The mean change in travel cost is \$59, \$64, and \$64 in the 2015, 2016, and 2017 BMM ride years respectively. Mean household income is \$128, \$139, and \$131 in 2015, 2106, and 2017 ride years. The estimation sample size is n=1545 with $n = 429$ BMM riders. Eighty-two percent of these riders are represented in the data for one survey year, 17% answered two surveys and 1% answered the survey after each BMM ride.

The monetary value of a revisit is the difference between what the consumer is willing and able to pay and the actual cost. In a simple linear logit model with just constant and slope terms, the monetary value (i.e., willingness to pay for the event) is the consumer surplus area from the probabilistic demand curve bounded by the probability of intended visitation at an additional travel cost of zero and the additional travel cost that makes this probability equal to zero. We estimate this consumer surplus with the same truncated willingness to pay formula used in Whitehead and Wicker (2019): $WTP = \frac{-1}{\beta_1} \ln\left(1 + \exp[\beta_0]\right)$. Alternative combinations of the stated preference and dichotomous choice dummy variable coefficients are included in the parenthetical term to estimate *WTP* under different valuation scenarios.

Results

We find that the coefficient on the change in the travel cost variable is negative and statistically significant in accordance with economic theory (Table 3). This finding is in accordance with economic theory and suggests that the results are internally valid – similar to previous research (Whitehead & Wicker, 2018, 2019, 2020). The income effect is positive, indicating that a return visit is a normal good. The additional travel cost variable is interacted with the dichotomous choice indicator variable for the 2016 survey. The coefficient on this variable is positive and statistically significant indicating that respondents are more likely to state that they will visit the following year with a dichotomous choice question. The coefficient on the stated preference dummy variable is positive and statistically significant, indicating that the stated preference data overstates actual return visitation behavior.

The standard deviation estimates give information about the level of preference heterogeneity. The standard deviation on the travel cost coefficient is about 69% of the coefficient, indicating that less than 7% of the individual conditional mean coefficient estimates are greater than zero (i.e., have the wrong sign). The standard deviation for the income coefficient is not statistically different from zero. The standard deviation of the change in travel cost and dichotomous choice interaction is equal to 81% of its coefficient, implying significant preference heterogeneity. The standard deviation of the stated preference dummy variable is 58% of the coefficient estimate. This indicates that less than 4% of the individual conditional mean coefficient estimates are less than zero indicating that the respondents understate their return visitation behavior. These results are somewhat different than Whitehead and Wicker (2019) statistically. More importantly, however, we find little practical difference in the results.

The four willingness to pay (WTP) estimates reflect all combinations of the question format (payment card and dichotomous choice) and the type of preferences assessed (stated and revealed preferences) (Table 4). Setting the stated preference variable equal to zero simulates the revealed preference value of a return visit estimated with the payment card question format. Standard errors are estimated using the Delta method. The baseline WTP ($SP = 0, DC = 0$) for a return visit is $16 which is 60% lower than the WTP estimate for a return visit to the Blood Sweat and Gears ride (Whitehead and Wicker 2019). This result makes sense given the greater demand for the Blood Sweat and Gears ride.

WTP estimated with the dichotomous choice question is no different than when estimated in the in the payment card format. This result contrasts with Whitehead and Wicker (2019) who found the payment card format to have higher WTP. Willingness to pay is $40 greater when the stated preference data is simulated ($SP = 1$). This result is similar to the results in Whitehead and Wicker, who find substantial hypothetical bias in willingness to pay. In a model where we code only “definitely yes” stated preference responses as participating in the future BMM the stated preference dummy variable is negative and statistically significant indicating that the stated preference data understates actual behavior. We do not present this model because the change in travel cost coefficient much more price inelastic, increasing the WTP estimates above those presented in Table 4, which does not make economic sense (i.e., lower demand generates greater *WTP*). These results are similar to Whitehead and Wicker (2019).

Aggregating the baseline willingness to pay estimate over the number of participants yields an aggregate economic value estimate of $11,143, $9735, and $6051 in the 2015, 2016 and 2017 BMM ride years respectively.

Conclusions

We find that the economic impact benefits of the micro-event the Beech Mountain Metric participatory bike race were $301,000 in 2014 to the local community, while the consumer surplus to participants was about $11,000. In 2015 the economic impact benefits were $273,000 while the consumer surplus benefits were less than $10,000. In 2016 the economic impact benefits had fallen to $185,000 while the consumer surplus benefits had fallen to under $8,000. The consumer surplus benefits are most likely relatively low in magnitude because there are many bike races in the region to choose from including Blood Sweat and Gears and the Blue Ridge Brutal, both more popular races. Also, the WTP estimates are for a return visit and subject to diminishing returns. The economic impacts benefits, however, are meaningful to a local economy, particularly during a slow time in tourism that occurs in May in the “High Country” region of North Carolina that depends upon tourism.

One important component of these types of studies, that Robert Baade has made clear over his many studies, is answering the question “Are the use of public funds efficient to support sports teams or pay for mega-events?” He finds that in most cases the use of public funds is not efficient. However, when looking at micro-events, it is likely that the only public funds used are the wages paid to police for their time closing the roads where the bike race takes place. These costs are much lower than the economic impact to the local community suggesting that the use of this police time is efficient.

Focusing on the stated benefits measure we replicate Whitehead and Wicker (2019) for the Beach Mountain Metric using the willingness to travel technique, 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. Consistent with Whitehead and Wicker (2019), we find substantial hypothetical bias in WTP models. This result suggests that the definitely yes and the sum of the probably and definitely yes probabilities provide a useful estimate of the range of return visitation that could be used in micro-event planning.

Our results suggest that a small scaled participatory athletic event or a micro-event, ones that are often ignored by politicians, might be the one area that the use of public funds might be efficient. As such, these types of events are worthy of more study.

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Figure 1. Beech Mountain Metric Willingness to Travel Survey Question

Suppose that you had to drive further to get to the Beech Mountain Metric in 2015 compared to your driving distance in 2014. For example, you might move further away from Beech Mountain.

Would you plan to participate in the 2015 Beech Mountain Metric at the following additional driving distances (one-way)?

	Definitely no	Probably no	Not sure	Probably yes	Definitely yes
30 more one-way miles					
60 more one-way miles					
90 more one-way miles					
120 more one-way miles					
150 more one-way miles					

Table 1. Beech Mountain Metric Surveys and Economic Impact			
	2014	2015	2016
Registered Participants	728	655	420
Completed Surveys	297	266	130
Response Rate	40.8%	40.6%	31.0%
Estimates:			
Participants	697	609	379
Non-local Participants	566	506	321
Individual Spending	$359	$365	$390
Aggregate Spending	$203,162	$184,717	$125,147
Economic Impact	$300,680	$273,382	$185,217

Table 2. Stated preference return visitation responses by Beech Mountain Metric ride year (combined probably yes and definitely yes responses)									
		2015		2016		2017			
		Payment Card		Payment Card		Payment Card		Dichotomous Choice	
	Distance	Yes (%)	n	Yes (%)	n	Yes (%)	n	Yes (%)	n
SP	0	83.48	224	85.33	184	85.71	56	94.12	51
SP	30	77.78	45	88.24	34	83.33	12	77.78	9
SP	60	66.00	50	60.00	45	78.57	14	81.82	11
SP	90	38.30	47	36.84	38	66.67	9	50.00	8
SP	120	31.11	45	28.95	38	16.67	12	33.33	3
SP	150	13.51	37	17.24	29	22.22	9	65.00	20
RP	0	45.54	224	41.30	184	42.86	56	31.37	51

Note: SP is stated preference and RP is revealed preference data.

Table 3. Random Parameter Logit Return Visitation Model						
	Definitely and Probably Yes (PYES)					
	Means			Standard Deviations		
	Coeff.	SE	t-stat	Coeff.	SE	t-stat
Constant	-0.7365	0.1163	-6.33	1.0460	0.0814	12.85
Change in travel cost (ΔTC)	-0.0341	0.0024	-14.36	0.0234	0.0025	9.21
Income	0.0031	0.0007	4.70	0.0004	0.0005	0.80
ΔTC x DC (=1)	0.0207	0.0047	4.39	0.0255	0.0076	3.36
SP (=1)	2.0566	0.1391	14.79	1.1974	0.1126	10.63
χ^2[df]	51.44[5]					
AIC	1717.10					
Observations	1545					
Riders	429					
Note: DC=dichotomous choice from Table 2						

Table 4. Willingness to pay estimates				
SP	DC	WTP	SE	t-stat
0	0	15.98	1.53	10.45
0	1	16.24	1.54	10.57
1	0	55.66	2.63	21.18
1	1	56.18	2.61	21.52
Note: DC=dichotomous choice from Table 2				