

## **Criterion and predictive validity of revealed and stated preference data: the case of “Mountain Home Music” concert demand**

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### **Abstract**

Despite a robust literature on nonmarket valuation of cultural assets, serious validity concerns remain. We address this by estimating a demand model for a regional concert series. We survey concertgoers during and then again after the concert season to gather ex ante and ex post stated and revealed preference data. Comparing ex ante stated preference data to ex post revealed preference data we find respondents overstate their concert attendance behavior. An ex ante revealed-stated preference demand model with a stated preference adjustment helps calibrate the results and avoid bias from using solely hypothetical, stated preference data. The results demonstrate how to improve predictive accuracy in contingent behavior models and improve our understanding of demand for live music performances.

*Keywords:* music demand, revealed preference, stated preference, criterion validity, predictive validity

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### **1. Introduction**

Better estimating the economic values of cultural assets can improve investments and understanding of demand in cultural industries. Yet these valuation exercises face inherent measurement challenges. Stronger evidence of the validity of stated preference (SP) and revealed preference (RP) data can further establish these tools' place in the field. We combine RP and SP

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data from a contingent behavior survey of a regional concert series to help calibrate the results and avoid bias from using solely hypothetical, SP data.

Economists have a strong preference for RP data, yet many situations lack sufficient RP information for economic analysis. For example, producers may desire *ex ante* information about how quantity demanded changes with price or how demand changes with quality. In these situations SP data may be useful. SP surveys can elicit hypothetical choices and behavior for various scenarios. Both types of data have limitations. RP data are limited to historical variation in prices and quality, and SP data are hypothetical and often biased in favor of good intentions. Combining RP and SP data can leverage both types' strengths: grounding results from SP surveys in the reality of RP while allowing variation beyond the range of prices and quality constrained by history (Whitehead et al. 2008b). The validity of the SP data remains a limiting factor. This study features a novel test of predictive validity, which compares the SP data with RP data gathered in a follow-up survey.

This study focuses on the Mountain Home Music (MHM) concert series, which features a variety of traditional regional (Appalachian) music styles at several locations in North Carolina. By surveying concertgoers both during and after the 2010 concert season, we gather RP and SP data during the concert season and additional RP data after the concert season. We find some evidence that combined revealed-stated preference models are predictive valid. While individual predictions are not criterion valid, our *ex ante* demand model with a SP adjustment predicts the actual number of concerts attended accurately.

## 2. Literature

Many studies apply nonmarket valuation techniques in the economics of cultural industries (Boter et al. 2005, Plaza 2010). Despite their prominence in the cultural sector, these economic valuation approaches face serious limitations. First, validity of SP data is often questioned (e.g., Noonan 2003, Plaza 2010, Hausman 2012). Applications of RP travel cost studies to the cultural sector are relatively new (e.g., Martin 1994, Forrest et al. 2000, Fonseca and Rebelo 2010, Vicente and Frutos 2011, Willis et al. 2012). Recent contingent behavior models (e.g., Alberini and Longo 2006) still face validity concerns. Measures like planned visits (Poor and Smith 2004) or previous visits (Melstrom 2013) may suffer from undue optimism or inflated recall. This study directly tests SP data validity and combines RP and SP data to correct for this sort of inflation of visit data. Secondly, it provides demand estimates for live music performances, adding to a handful of previous studies (e.g., Bedate et al. 2004).

Criterion validity is the accuracy of a SP measure of value or behavior compared to the actual value or behavior. Many contingent valuation studies compare hypothetical (from surveys) and actual (from laboratory or field experiments) willingness to pay. Divergence in actual and hypothetical values is evidence of hypothetical bias. Meta analyses (List and Gallet 2001, Murphy et al. 2005) suggest that private goods and behavior leading to use value generate less hypothetical bias. The contingent behavior literature has several tests of criterion validity. Dickie et al. (1987) and Loomis (1993) find no statistically significant difference between SP and RP estimates, whereas Whitehead (2005) finds SP behavior significantly overstates responsiveness.

In contrast to criterion validity, predictive validity is the ability of the SP data to accurately predict RP outcomes. The literature includes two applications of predictive validity tests. Grijalva et al. (2002) conduct a predictive validity test for rock climbing trip behavior. They compare survey respondents' *ex ante*, hypothetical SP trip behavior with their RP trip behavior after some

rock climbing areas actually closed. RP trip behavior changed in the expected direction. Whitehead (2005) assesses predictive validity regarding hurricane evacuation behavior using surveys before and after hurricanes. Models using RP and SP evacuation data forecast behavior with less prediction error than models that solely rely on RP or SP data.

Predictive validity can be assessed by jointly estimating the behavior model with both types of preference data in a single equation. RP and SP data can differ in demand intercepts and slopes (Whitehead et al. 2008a). Typically, SP demand is higher and more elastic as respondents may be motivated by good intentions in terms of consumption levels and responsiveness. A simple correction for these hypothetical biases sets the SP dummy variable equal to zero. The resulting “simulated revealed preference” demand may be devoid of the hypothetical bias.

### 3. Survey and data

The data to assesses criterion and predictive validity come from a survey administered online to MHM concert attendees. We visited ten regular season MHM concerts from May to December 2010 (see Table 1) and asked concertgoers for an email address so we could email them the link to the survey. The surveys were sent in the week following the concert, and a follow-up email was sent to nonrespondents a week later. An average of 13 people per concert gave their email addresses, and the response rate was about 70% of those who had agreed to be surveyed. A total of 83 usable responses were collected. (The potentially nonrepresentative sample does not affect our tests of criterion and predictive validity.)

Table 1. Concert Attendance and Survey Response Rates

Date	Attendance	Sample Size	Survey Responses	Response Rate (%)
30-May	225	na	10	na
5-Jun	93	12	10	83
12-Jun	182	5	4	80
19-Jun	74	7	5	71
26-Jun	161	14	12	85
3-Jul	440	na	na	na
25-Jul	151	na	na	na
7-Aug	145	11	6	54
14-Aug	134	na	na	na
22-Aug	275	na	na	na
5-Sep	212	22	18	81
9-Oct	98	21	14	67
16-Oct	110	13	6	46
27-Nov	71	na	na	na
18 – Dec	150	12	9	75
Total	2521	127	94	74

The survey asked questions about which concerts the respondents had already attended during the current 2010 season and how many they attended in the 2009 season in order to establish a baseline, RP set of data. Respondents were asked to indicate which concerts they planned on attending for the rest of the 2010 season assuming the price stayed the same. The 2010 concert demand variable is thus a mixture of RP and SP data. Respondents were asked for the number of concerts attended during a typical season, and contingent behavior questions asked for the number of concerts respondents would attend if the price increased by \$3 and then by \$10. All of these responses created a pseudo-panel dataset with five observations per respondent for a total of 415 observations.

After the season's last concert in December, a final survey was sent to everyone who had responded to the original survey. It asked people which concerts they had attended during the 2010 season, generating a set of RP data that can be compared to the SP data from the original surveys. Out of about 120 people who were sent the follow-up survey, 60 responded for a 50% response rate, but only 38 responses were usable. Unusable responses include respondents who attended the last concert (and thus lack SP concert information for the rest of the season) and respondents with missing concert data. Four respondents indicated in their in-season survey a number of concerts attended that was one greater than the number indicated in their post-season survey. These concertgoers may suffer from recall bias (i.e., they forgot about a concert they attended). We recode their postseason RP concerts by adding one.

For those who answered the follow-up survey, the average number of concerts attended in 2009 is four (Table 2), slightly less than the typical 4.8. The sum of the RP and SP concerts in the current year (2010) is 5.74. Thirty-five percent of these responses are RP. With a \$3 ticket price increase (i.e., a 20% increase from the \$15 price) the number of concerts falls by 24% from the current year. With a \$10 ticket price increase (i.e., a 67% increase) attendance falls by 45% from the current year. Those who attended the final concert or did not answer the follow-up survey are more avid concertgoers with more inelastic demand. They averaged almost five concerts in 2009 and almost six (RP and SP) concerts in the current year. With a \$3 or \$10 price increase, their attendance falls by only about 4% or 26%, respectively.

Table 2. Concert Demand Data

Scenario	Year	Price	Stated Preference	Typical	Follow-up Survey Respondents (n=38)			
					Stated Preference		Concerts	
					Mean	StdDev	Mean	StdDev
1	2009	15	0	0	0		4.05	2.44
2	2010	15	0.65	0	0.65	0.30	5.74	3.14
3	"Typical"	15	1	1	0		4.79	2.21
4	2011	18	1	0	1		4.34	1.98
5	2011	25	1	0	1		3.18	1.78
6	2010	15	0	0	0		3.58	2.13

  

Scenario	Year	Price	Stated Preference	Typical	Follow-up Survey Nonrespondents (n=45)			
					Stated Preference		Concerts	
					Mean	StdDev	Mean	StdDev
1	2009	15	0	0	0		4.73	4.74
2	2010	15	0.45	0	0.45	0.35	5.91	5.32
3	"Typical"	15	1	1	0		6.00	4.63
4	2011	18	1	0	1		5.67	4.62
5	2011	25	1	0	1		4.36	4.25

#### 4. Empirical results

We first consider criterion validity. We test for the statistical significance of the difference in SP and RP concerts by considering the difference in postseason RP concerts and the sum of in-season RP and SP concerts,  $\Delta Q = Q_T^{rp} - (Q_t^{rp} + Q_t^{sp})$ , where  $t = 1, \dots, 8$  surveyed concerts with postseason survey respondents and  $T$  is the end of the concert season. Of the  $n = 38$  respondents to the follow-up survey,  $n = 2$  correctly predicted and  $n = 5$  understated the number of concerts they would attend by season's end. The mean concert difference is a 2.26 overstatement with a median of 2, mode of 1, minimum of -5 and maximum of 8 concerts. The difference-in-means test indicates that the difference is significantly different from zero at the  $p=.01$  level ( $t=5.51$ ). The nonparametric signed rank test indicates that the difference is significantly different from zero at the  $p=.01$  level ( $S=271$ ).

Regressing the difference in RP trips over the course of the season,  $\Delta Q^{rp} = Q_T^{rp} - Q_t^{rp}$ , on SP trips,  $Q_t^{sp}$ , shows that the overstatement increases with the number of SP trips with no constant overstatement:  $\Delta Q^{rp} = 0.16(0.44) - 0.42(0.08) \times Q_t^{sp}; R^2 = 0.41$ , where the numbers in parentheses are standard errors. The inverse of the coefficient on SP concerts equals the univariate mean concert overstatement. An important feature of our research design is that some respondents were interviewed earlier in the concert season than others, allowing them more scope for guesswork and hypothetical bias from good intentions. Regressing hypothetical bias (i.e., the difference in the number of revealed and stated concerts),  $HB = Q_t^{sp} - \Delta Q^{rp}$ , on the portion of

the concert season covered by the stated preference question,  $SP$ , shows that the errors are increasing in the opportunity for errors:  $HB = -0.46(0.85) + 4.22(1.19) \times SP$ ;  $R^2 = 0.26$ . Various socioeconomic variables (e.g., age, household size) are included in each of these models and no effect is found.

Next we consider predictive validity. The survey provides five data points linking price with quantity for every respondent: one RP quantity at the actual price, one combination RP and SP quantity at the actual price, one typical quantity at the actual price, and two SP quantities at hypothetical higher prices. We estimate fixed effects Poisson panel data models (Englin and Cameron 1996):

$$\ln Quantity_{it} = \alpha_i + \beta_P Price + \beta_{SP} SP + \beta_T Typical + \varepsilon_{it} \quad (1)$$

The fixed effects model for individual  $i$  and scenario  $t$  employs an implicit individual-specific constant term,  $\alpha_i$ . The independent variables are those that change across scenarios for each individual: price, SP scenarios, and the “typical” concert scenario. The marginal effects of each variable on the number of concerts is  $\frac{\partial Q}{\partial X} = \beta_X \bar{Q}$ , where  $Q$  is quantity and  $X$  is an independent variable.

Table 3 presents regression results. Survey respondents in both samples have downward sloping demand functions with negative and statistically significant price coefficients. The demand elasticities for follow-up survey respondents and other respondents are  $e_P = -1.02$  and  $e_P = -0.66$ , respectively. These elasticities are consistent with Table 2. If  $\beta_P$  was a function of price, then average elasticity might differ from this. These data do not permit  $\beta_P$  to vary by price. The “typical” season coefficient is insignificant for follow-up survey respondents. The “typical” season marginal effect suggests that other respondents attend 1.21 more concerts each year than their RP concert attendance suggests. The marginal effects of the SP scenarios on concert attendance are about 1.7. Considering follow-up survey respondents, the 95% confidence interval for the marginal effect is [0.73, 2.67]. Considering their responses to the follow-up survey, the mean concert attendance difference of 2.26 is within the confidence interval predicted from the empirical model that does not use the postseason data. A standard correction for hypothetical bias of setting the SP dummy variable equal to zero would produce accurate forecasts of postseason concerts.

Because a log-linear model is used, the inverse of the coefficient on price is an estimate of the consumer surplus per concert attended,  $CS = -\frac{1}{\beta}$ . The demand model yields a consumer surplus of \$15 for follow-up survey respondents and \$23 for other respondents. This exceeds Bedate et al.’s (2004) Spanish organ festival estimates, but aligns well with CS estimates for other cultural site visits (Poor and Smith 2004, Alberini and Longo 2006). Although not affecting the validity tests here, the potentially unrepresentative sample does warrant caution in generalizing from these CS estimates.

Table 3. Fixed Effects Concert Demand Models

	Follow-up Survey Respondents (n=38)					
	Coefficient	SE	Coeff/SE	Marginal Effects	95% Confidence Interval	
PRICE	-0.068	0.013	-5.330	-0.303	-0.414	-0.191
SP	0.385	0.112	3.440	1.703	0.734	2.673
TYPICAL=1	0.161	0.105	1.530	0.712	-0.198	1.622
LL	-239.19					
AIC	484.40					
Cases	38					
Periods	5					
	Other Respondents (n=45)					
	Coefficient	SE	Coeff/SE	Marginal Effects	95% Confidence Interval	
PRICE	-0.044	0.011	-4.040	-0.232	-0.345	-0.120
SP	0.331	0.095	3.480	1.766	0.771	2.760
TYPICAL=1	0.227	0.085	2.680	1.213	0.326	2.100
LL	-93.94					
AIC	593.90					
Cases	45					
Periods	5					

## 5. Conclusions

Despite its popularity in cultural economics, Hausman (2012) condemns SP data for hypothetical bias. Relative to contingent valuation there are very few contingent behavior studies where tests for hypothetical bias are even possible because of context and data limitations. We conduct a unique in-season and postseason survey to test the predictive validity of SP survey responses. This is a rare opportunity to apply it, and a novel opportunity in the cultural field. We find that SP concert attendance data lack criterion validity. Respondents tend to overstate their concert attendance behavior. Respondents are generally accurate, however, when predicting their own behavior *after* a statistical adjustment for hypothetical bias. This predictive validity lends some confidence to using SP data in the cultural sector.

Beyond its relevance to the broader nonmarket valuation literature, this study's findings hold additional interest for the cultural economics field. This approach shows valid measures of consumer surpluses using hypothetical price changes for a regional music concert series. Live music performances face economic challenges in overcoming Baumol's cost disease and identifying optimal pricing in light of prerecorded music. The evidence here suggests that combining RP and SP data can shed light on these practical questions for music festivals. Correcting for hypothetical bias and improving predictive validity enables better estimates of demand and predictions of behavioral responses using *ex ante* information for music or other cultural goods.

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## References

- Alberini, A. and Longo, A. (2006) Combining the travel cost and contingent behavior methods to value cultural heritage sites: Evidence from Armenia, *Journal of Cultural Economics*, 30(4), 287-304.
- Bedate, A., Herrero, L.C. and Sanz, J.A. (2004) Economic valuation of the cultural heritage: application to four case studies in Spain, *Journal of Cultural Heritage*, 5, 101-111.
- Boter, J., Rouwendal, J. and Wedel, M. (2005) Employing travel time to compare the value of competing cultural organizations, *Journal of Cultural Economics*, 29(1), 19-33.
- Dickie, M., Fisher, A. and Gerking, S. (1987) Market transactions and hypothetical demand data: a comparative study, *Journal of the American Statistical Association*, 82(397), 69-75.
- Englin, J. and Cameron, T.A. (1996) Augmenting travel cost models with contingent behavior data, *Environmental and Resource Economics*, 7(2), 133-147.
- Fonseca, S. and Rebelo, J. (2010) Economic valuation of cultural heritage: application to a museum located in the Alto Douro Wine Region– World Heritage Site”, *Pasos* 8(2), 339-350.
- Forrest, D., Grimes, K. and Woods, R. (2000) Is it worth subsidizing regional repertory theatre?, *Oxford Economic Papers*, 52, 381-397.
- Grijalva, T., Berrens, R., Bohara, A. and Shaw, D. (2002) Testing the validity of contingent behavior trip responses, *American Journal of Agricultural Economics*, 84(2), 401-414.
- Hausman, J. (2012) Contingent valuation: from dubious to hopeless, *Journal of Economic Perspectives*, 26(4), 43-56.
- List, J.A. and Gallet, C. (2001) What experimental protocol influence disparities between actual and hypothetical stated values?, *Environmental and Resource Economics*, 20(3), 241-254.
- Loomis, J.B. (1993) An investigation into the reliability of intended visitation data, *Environmental and Resource Economics*, 3, 183-191.
- Martin, F. (1994) Determining the size of museum subsidies, *Journal of Cultural Economics*, 18(4), 255-270.
- Melstrom, R.T. (2013) Valuing historic battlefields: an application of the travel cost method to three American Civil War battlefields, *Journal of Cultural Economics*, forthcoming. DOI: 10.1007/s10824-013-9209-7.
- Murphy, J.J., Allen, P.G., Stevens, T.H. and Weatherhead, D. (2005) A meta-analysis of hypothetical bias in stated preference valuation, *Environmental and Resource Economics*, 30(3), 313-325.
- Noonan, D.S. (2003) Contingent valuation and cultural resources: a meta-analytic review of the literature, *Journal of Cultural Economics*, 27(3-4), 159-176.
- Plaza, B. (2010) Valuing museums as economic engines: willingness to pay or discounting of cash-flows?, *Journal of Cultural Heritage*, 11, 155-162.
- Poor, P.J. and Smith, J.M. (2004) Travel cost analysis of a cultural heritage site: the case of historic St. Mary’s City of Maryland, *Journal of Cultural Economics*, 28, 217-229.
- Vicente, E. and de Frutos, P. (2011) Application of the travel cost method to estimate the economic value of cultural goods: blockbuster art exhibitions, *Hacienda Pública Española / Revista de Economía Pública*, 196(1), 37-63.

- Whitehead, J.C. (2005) Environmental risk and averting behavior: predictive validity of jointly estimated revealed and stated behavior data, *Environmental and Resource Economics*, 32, 301-316.
- Whitehead, J.C., Dumas, C.F., Herstine, J., Hill, J. and Buerger, B. (2008a) Valuing beach access and width with revealed and stated preference data, *Marine Resource Economics*, 23, 119-135.
- Whitehead, J.C., Pattanayak, S., Van Houtven, G. and Gelso, S. (2008b) Combining revealed and stated preference data to estimate the nonmarket value of ecological services: an assessment of the State of the Science, *Journal of Economic Surveys*, 22(5): 872-908.
- Willis, K.G., Snowball, J.D., Wymer, C. and Grisolia, J. (2012) A count data travel cost model of theatre demand using aggregate theatre booking data, *Journal of Cultural Economics*, 36, 91-112.