ISSN 1988-088X

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DFAE-II WP Series

2012-01

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Forecasting accuracy of behavioural models for participation in the arts

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Abstract:

In this paper, we assess the forecasting performance of count data models applied to arts attendance. We estimate participation models for two artistic activities that differ in their degree of popularity -museum and jazz concerts- with data derived from the 2002 release of the *Survey of Public Participation in the Arts* for the United States. We estimate a finite mixture model – a zero-inflated negative binomial model - that allows us to distinguish "true" non-attendants and "goers" and their respective behaviour regarding participation in the arts. We evaluate the predictive (in-sample) and forecasting (out-of-sample) accuracy of the estimated models using bootstrapping techniques to compute the Brier score. Overall, the results indicate good properties of the model in terms of forecasting. Finally, we derive some policy implications from the forecasting capacity of the models, which allows for identification of target populations.

Keywords: *Forecasting; count data; prediction intervals; Brier scores; bootstrapping; art participation.*

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* Corresponding author. A first version of this paper was presented at the University of Catania, 2011 and at the fifth European Workshop on Applied Cultural Economics in Dublin, 2011. The authors are grateful to all participants for comments, and are especially indebted to Roberto Zanola. The usual disclaimers apply.

1. Introduction

Cultural economics has contributed to our knowledge on participation in the arts by proposing and estimating economic models to explain the determinants of demand for cultural goods and services. Art managers have focused their interest on knowledge of their participants to design and implement effective marketing strategies for different artistic goods. In this paper, we try to relate both types of contributions by estimating a participation model and assessing its properties in terms of forecasting of cultural participation in jazz concerts and museum visits.

Participation in the arts, together with the consumption of cultural goods, corresponds to the last stage of the cultural process, as defined by UNESCO (2009). It includes the activities of audiences and participants in consuming cultural products and taking part in cultural activities and experiences. Traditionally, participation in the arts has been divided into three categories depending on the way in which it takes place: attendance, active practice and the consumption of cultural content through the media. The research interest of the field of cultural participation has gone through several stages, with each providing different types of knowledge on audience composition and motivation, which has added to previous contributions.

First, general descriptions of the socio-economic characteristics of the audiences with respect to non-audiences were explored. As noted in Seaman (2005) and McCarthy *et al.* (2001), the initial interest was set on determining who was participating in the arts, and initial studies thus provided a description of which social groups participate more in relative terms, shedding light on the composition of audiences. That set of initial studies (participation studies; Seaman, 2005) confirmed some common traits of cultural audiences: audiences are more educated and enjoy higher income, there is evidence of some feminisation in the arts audiences, and attendance is a mostly urban phenomenon. Those studies also reported that no particularities were found for different countries.

In a second step, a different set of studies (econometric studies, such as those reported in the survey by Seaman, 2005) began to incorporate individual decision-making models to understand why people participate in the arts and why differences arise. This type of study tries to estimate demand functions when price and income information is available (see, e.g. Prieto-Rodriguez *et al.* 2005). Own-price elasticity, income (full-income) elasticity and the degree of complementarity-substitutability were researched. When modelling and estimating the demand for cultural goods, economists consider that factors others than prices and income determine the choice set of the cultural consumer and, subsequently, consumer demand. Additionally, the determinants of underlying tastes and its possible evolution are taken into account by some of those models. Notably, the presence of a certain stock of personal capital in terms of the ability to interpret and enjoy the symbolic characteristics of goods is considered. In this spirit, early exposure to the arts and artistic training are introduced in those individual decision models.

When prices and/or personal income are not available, participation equations are estimated to determine how personal constraints – in the form of personal capital / education, income, household burdens and so on – shape the observed choice of attendance. Participation equations, with the first equations in the form of probit/logit regression models, quantify the effect of marginal changes in the explanatory variables on the probability of being an attendee over a determined period of time (Gray 2003). The intensity of participation has sometimes been modelled by means of ordered probit/logit models (Borgonovi 2004). Unobserved heterogeneity that may induce different behavioural patterns in the observed choice of the population has been addressed by latent class models (Ateca-Amestoy 2008; Fernandez-Blanco et al. 2009). The testable hypotheses derived from the economic approach to cultural participation have thus been tested by estimating those types of econometric models using a wide variety of information on the cultural habits of the general population. Behavioural models not only assess the correlates of participation but also explain the determinants of those observed choices based on individual decision-making models.

However, in cultural economics, the forecasting properties of those behavioural estimated participation models have rarely been assessed. For instance, little attention has been devoted to the appropriateness of the models to describe what happens outside the sample used in the estimation: do people not included in the survey really behave as the estimated models establish? Moreover, the accuracy of the models is not often even assessed for those in the sample; researchers were more concerned with determining the relevant characteristics of participants rather than fully predicting their behaviours with regard to cultural participation. This can be thought of as an additional step of a study programme that has already systematically analysed the behaviour, as a model is needed to contrast it against reality in terms of its forecasting power, that is, its capacity to predict behaviour for those individuals not included in the sample used to estimate the model.

The achievement of this further step is interesting not only for researchers in cultural economics but also for cultural managers who attempt to better understand the characteristics of their audiences and the general population. We believe that a deeper knowledge may contribute to improving the targeting of audiences and lead to the more efficient programming and promotion of cultural activities.

The forecasting of future attendance in the area of cultural goods and services has been performed using different methods in the field of cultural management. One method corresponds to a consumer-oriented approach (Andreasen and Belk 1980; National Endowment for the Arts 1981; Holbrook and Schindler 1994). This approach is based on the correlates of attendance, including attitudinal values, determinants of lifestyles and early exposure. However, because this approach does not always deal properly with endogeneity problems and causation, the usefulness of the findings for policy making cannot be addressed. A second approach focuses on the characteristics of the cultural event to forecast its audience. Some studies have taken a "manipulative approach to check the declare effect on future participation of a change in the attributes of the event" (National Endowment for the Arts 1981). Potential sales equations can be estimated, and the results are compared with expert forecasts (Putler and Lele 2003). Expert forecasts are part of the "managerial approach". Based on combinations of different techniques, such as the Delphi approach or forecasts based on the expertise of the managers, the potential audience of a particular event is estimated. This is one of the methods explored in the ARTSplan program (Weinberg 1986; Weinberg and Shachmut 1978). Finally, Jones *et al.* (2007) used goal programming models to identify whether an individual ever goes to a movie theatre or does not using UK data.

In this paper, we want to explore the possibility of using behavioural models to gain further knowledge of consumers of art and to assess the predictive and forecasting performance of behavioural participation models applied to arts attendance. If behavioural models perform well in terms of forecasting, they will be useful for predicting potential and future attendance. To verify the robustness of our findings, we have decided to analyse two different cultural activities: attendance at jazz concerts and visiting art museums and art galleries. There are obvious differences between these activities, as one is a performing arts activity and the other one is related to the appreciation of cultural heritage. The dependent variable is defined as the number of times that a particular individual attends a museum or a live jazz performance.

Given this information, we estimate finite mixture models that allow us to distinguish "true" non-attendants and "goers" (even if they may show a zero corner behaviour). In doing so, we use data derived from the 2002 release of the *Survey of Public Participation in the Arts* (SPPA) for the United States. Furthermore, we evaluate the predictive (in-sample) and forecasting (out-of-sample) accuracy of the estimated models using bootstrapping techniques and computing Brier scores.

The paper is organised as follows. Section 2 discusses the data and the econometric issues in estimating cultural participation using finite mixture models. Section 3 discusses estimation results and includes a brief interpretation of the findings. The analysis of the forecasting power of the model using bootstrapping techniques to compute the Brier score is discussed in Section 4. Conclusions are discussed in Section 5.

2. Material and methods

We perform our empirical exercise on the data derived from the 2002 release of the *Survey of Public Participation in the Arts*. This is a dataset that compiled information on different types of cultural participation for the United States between 1 August 2001 and 1 August 2002. It was the fifth study in a series conducted by the *Bureau of the Census* for the *National Endowment for the Arts* (NEA) since 1982 and was run as a supplement to the *Current Population Survey* (Bureau of the Census 2003). A total of 17,135 individual questionnaires were completed for a representative sample of households in the US. In each of the selected households, all individuals over 18 were interviewed, and information is thus directly reported by each individual in this edition of the survey.[1]

The NEA defines seven benchmark activities out of which six refer to performing arts and only one to heritage access. The main descriptives of these activities are presented in Table 1.

[1] This was not the case in the 2008 *Survey of Public Participation in the Arts*, where individual attendance information about members of the household was reported by the one selected as the reference person (National Endowment for the Arts 2010, 2004). We rather use the 2002 survey in order to limit potential measurement errors since our aim is to explore the forecasting power of the behavioural models.

Table 1
Average attendance to benchmark activities in the United States.[2]
Data derived from the *Survey of Public Participation in the Arts*, 2002.

BENCHMARK ACTIVITIES	PROPORTION OR AVERAGE	STANDARD ERROR
PERFORMING ARTS		
Jazz		
Go jazz	0,108	0,003
Number of times (sample)	0,331	0,017
Number of times (goers)	3,104	0,13929
Classical music		
Go classical music	0,116	0,003
Number of times (sample)	0,351	0,019
Number of times (goers)	3,063	0,148
Opera		
Go opera	0,032	0,002
Number of times (sample)	0,063	0,005
Number of times (goers)	2,002	0,125
Musicals		
Go musicals	0,171	0,003
Number of times (sample)	0,058	0,006
Number of times (goers)	3,018	0,241
Non-musical theatre		
Go theatre	0,123	0,003
Number of times (sample)	0,285	0,011
Number of times (goers)	2,332	0,072
Dance and ballet		
Go dance and ballet	0,087	0,003
Number of times (sample)	0,192	0,009
Number of times (goers)	2,034	0,104
HERITAGE ACCESS		
Museum and art galleries		
Go museum and art galleries	0,265	0,004
Number of times (sample)	0,925	0,047
Number of times (goers)	3,509	0,171

For our empirical exercise we select visits to museums and art galleries and attendance to jazz concerts. By using this selection we are able to compare heritage and performing arts activities. Furthermore, within performing arts attendance to jazz concerts has some special characteristics that we believe that make it a good candidate for this exercises: first, it is quite popular in terms of percentage rate of attendance and, second, it has the largest dispersion in the number of times among attendees.

We show in Table 2 the distribution of answers for the number of times that the individual reported having attended a jazz concert and/or a museum or art gallery during the previous 12 months, which are the dependent variables under consideration. Some

[2] As defined by the National Endowment for the Arts.

features are observed. For instance, no-attendees are more common than participants for both activities, although museums are more popular than jazz concerts; those who go to jazz concerts represent one third of those who visit museums and art galleries. Therefore, although, as expected, there are some similarities between these two cultural activities, which are confirmed by the Pearson correlation coefficient, there are also significant differences, thus making them good candidates with which verify the robustness of our proposal.

Table 2
Museums and art gallery visits and jazz performance attendance over the last year

	Art museum & galleries												
Jazz	0	1	2	3	4	5	6	7	8	9	10	> 10	Total
0	11,840	1,469	903	411	204	106	109	19	24	6	40	112	15,243
1	281	130	117	75	32	22	15	1	2	0	7	25	707
2	150	74	89	54	22	24	17	2	2	0	10	18	462
3	70	29	41	27	23	9	9	2	3	0	9	20	242
4	29	13	22	8	13	4	4	0	3	0	4	9	109
5	17	5	12	6	5	5	8	0	0	0	5	5	68
6	17	9	8	7	1	1	6	0	1	0	1	8	59
7	1	0	0	0	0	1	0	0	0	0	0	0	2
8	4	2	0	0	4	3	1	0	0	0	0	0	14
9	0	0	0	1	0	0	0	0	0	1	0	1	3
10	6	0	5	2	3	1	4	0	0	1	0	5	27
More than 10	8	8	7	5	6	5	4	0	0	0	2	11	56
Total	12,423	1,739	1,204	596	313	181	177	24	35	8	78	214	16,992
Pearson $\chi^2(1) = 3603.11$													

Using these two dependent variables, we estimate participation equations for jazz concerts and visits to museums and art galleries. The dependent variable is the number of times that the individual declared in the survey to have gone to a jazz concert (museum or art gallery) during the previous year. Two separate count models are estimated for each of these activities. We use the count nature of the variable that is elicited to measure attendance.

Following standard empirical specifications in the literature, attendance at any of the two cultural activities that we explore is assumed to depend on personal and contextual factors that determine that the optimal choice of the individual is to attend jazz concerts or museums a given number of times.

$$y_i = f\left(\mathbf{x}_i\right) = f\left(S_i, Se_i, De_i, H_i, E_i\right)$$

Among those factors, S_i represents variables related to the stock of available cultural capital, determined by one's own general education, education transmitted by parents, early exposure to the arts and specific artistic training of some sort. Se_i, De_i and H_i provide information about the socioeconomic and demographic characteristics of the individual and his/her household, such as sex, age, race, occupational status, marital status, household size and family income. Finally, E_i denotes the geographical variable, which allows us to incorporate contextual effects such as the size of the habitat. The vector of explanatory variables is detailed in Table A1 in the Appendix, where the main descriptive statistics are also presented.

We proceed by estimating a simple count model that explains the number of times that the individual reports to have attended that activity during the last past 12 months; a Poisson regression model and a goodness of fit test used to determine equidispersion (i.e., equality of mean and variance) are conducted. Because the hypothesis is rejected, we estimate a negative binomial regression model. Still, we find that unobserved heterogeneity may lead to a bad fit. Recall from Table 1 above that 12,423 individuals out of 16,992 reported not having attended any museum or art gallery during the previous year and that 15,243 out of 16,992 declared that they had not gone to any jazz concerts in that period. Therefore, given the evidence of overdispersion and excess zeros, which could be due to unobserved heterogeneity, the model that is chosen to explain both types of attendance is a zero-inflated negative binomial model.

This model allows us to separate two different data-generating processes: one that determines the probability of an individual being a never-goer (the never-goer is a qualified no-goer), and another that determines the probability of an individual attending a positive number of times (some of the zeros are zero-corner solutions that have a non-zero probability of being attendants). Belonging to either of those groups is determined by a latent binary process (in our case, a logit model), and the behaviour of the zero-corner solutions and of the positive counts is ruled by a negative binomial process. The former binary process determines the inflation part of the model, and we estimate the effect of each of the covariates over the probability of being a never-goer. The latter count process is estimated to obtain the effect of each of the explanatory variables over the probability of attending a given number of times.[3] In the following section, we present the results of the estimated models.

3. Estimations results

For the subpopulation of never-goers, the only possible outcome is zero times. For the other subpopulation, we use the zero-to-positive count, which represents the likely number of times that the individual attending is ruled by a negative binomial process. As we use the same set of explanatory variables for both processes, this allows us to separate the potential effect of each variable through the inflation and/or the count equations. Our findings for museums and art galleries and for jazz concerts are now briefly discussed. As mentioned previously, these activities were selected on the basis of the observed heterogeneous participation patterns. Accordingly, as presented below, the results of the estimated models are also different.

The inflation equation of the museum and art gallery model provides us with the following results. There is a negative monotonic and significant effect of the variables that represent cultural personal capital over the probability of never attending. We find evidence supporting the relevance of personal education –both formal and specific artistic education- and for the contribution of parental education to the intergenerational transmission of cultural capital (both the father's -except for the less than high school category- and mother's education have a monotonic negative and significant effect on the probability of never going). Gender effects also operate in the inflation part of the model; being male increases the probability of never going to museums. We do not find consistent age effects, except for individuals in the 45-54 interval (negative effect on inflation). However, being retired has a positive effect over the inflation with respect to the baseline of working full-time. With respect to being married, every other possible marital status is associated with a higher probability of never going. Income is a significant variable in the inflation; there are monotonic negative and significant effects of household income, even if the magnitude of this variable is somehow smaller than the magnitude of cultural capital variables.

[3] For a complete description of the underlying behavioural assumptions of using a latent class model, see Ateca-Amestoy (2008) and Fernández-Blanco, *et al.* (2009). Ateca-Amestoy (2008) further discusses the selection criteria among count data models: Poisson and negative binomial, and zero inflated and hurdle models.

For the count part that explains the probability of a higher frequency of attendance, we find significant and positive effects for education, especially among the upper extreme categories (university degree) for both one's own and parental education. Regarding the specific artistic cultural capital, we find positive effects for art and visual art classes but negative effects for music appreciation classes (potentially signalling some sort of specialisation in the acquisition of this very specific sort of cultural capital). There are no gender effects on intensity, and age, when it is significant, has a positive monotonic effect. Ethnicity variables have a negative effect over intensity for blacks and for islanders with respect to whites; therefore, the ethnic effect seems to affect the number of visits but not whether a particular person can be classified as a non-attendant. Fewer jobs and familiar burdens seem to be positively associated with more frequent visits (the positive effect of working part-time and of being single, and the negative effect of the household size). Curiously, the only statistically significant effect of habitat size is in the count part of the model. With respect to individuals living in metropolitan areas, those living in central areas (as defined in terms of the SPPA codification by the American Bureau of the Census) are more likely to go more often. We may conjuncture a twofold explanation: first, museums and art galleries are a cultural infrastructure that is much more frequented than others; second, museum attendance is highly linked with tourist habits. In accordance with this second explanation, there is not a strict correspondence between the availability of museums and arts galleries in one's place of residence and the possibility of visiting museums when engaging in tourism.

The characterisation of the jazz concert estimation proceeds as follows. The inflation aspect of the jazz participation model is also ruled by important cultural capital effects. Again, both one's own general education and specific artistic training (though not music lessons) have a monotonic negative effect on the probability of never going. Parental education effects are also present and, as before, are of a smaller magnitude compared to one's own education. Ethnic differences in the inflation portion determine a lower probability of not attending for blacks and a higher probability for Asians and Pacific islanders. Income has a monotonic and significant effect on inflation, revealing a lower probability of never going as income increases. Central habitat has also a negative influence on the inflation.

The count equation of the jazz model explains the probability of higher counts among attendees. We find a positive effect of specific music training, which is the sole variable related to cultural capital that has a significant effect on the intensity of attendance. There is a positive gender effect for men, no clear age effects and a negative effect of being unemployed (with respect to full-time employment). As expected, lower family burdens are associated with higher attendance; divorced individuals show a higher probability of greater participation, and household size has a negative effect on the number of concerts attended. When considering metropolitan MSA, the effect with respect to metropolitan residence is positive. This result suggests that a higher frequency of attendance is linked to smaller supply restrictions in those places with higher variety and bigger populations, a principle that applies only to those individuals who belong to the class of goers.

Overall, we can highlight the relevance of income and, more importantly, that of cultural capital as determinants of the inflation part of the model. The highest levels of education and some determinants of specific cultural capital also operate on the frequency of attendance as well as the variables related to time availability.

Table 3
Estimation results

	Art museum & galleries		Jazz concerts	
	Count	**Inflation**	**Count**	**Inflation**
edu1	0.01023	0.42410**	0.08728	0.71876***
	[0.05]	[2.20]	[0.28]	[3.14]
edu3	0.16443	-0.62062***	0.17176	-0.41713**
	[1.55]	[-4.34]	[1.22]	[-2.27]
edu4	0.49791***	-0.91577***	0.03351	-0.86992***
	[4.30]	[-4.77]	[0.25]	[-4.61]
edu5	0.63890***	-1.67404***	0.30571	-1.10825***
	[6.88]	[-5.64]	[1.63]	[-4.05]
fatheredu1	-0.27055***	-0.39238***	-0.15795	-0.19123
	[-3.63]	[-2.74]	[-0.86]	[-0.91]
fatheredu3	-0.05695	-0.73026***	-0.19839	-0.10765
	[-0.69]	[-3.46]	[-1.37]	[-0.54]
fatheredu4	0.09173	-0.47637*	0.11971	-0.40270**
	[0.84]	[-1.93]	[0.96]	[-2.05]
fatheredu5	0.19309**	-1.48619***	0.15283	-0.56041**
	[1.98]	[-3.16]	[1.13]	[-2.40]
motheredu1	-0.00415	0.0878	0.06922	0.307
	[-0.05]	[0.55]	[0.44]	[1.56]
motheredu3	0.026	-0.49932**	0.15215	-0.36841*
	[0.32]	[-2.30]	[1.20]	[-1.68]
motheredu4	0.16424*	-0.38964*	0.05005	-0.46894*
	[1.94]	[-1.72]	[0.38]	[-1.73]
motheredu5	0.24700*	-0.83690*	0.09055	-0.51750*
	[1.96]	[-1.71]	[0.49]	[-1.82]
classmusic	0.0376	-0.71256***	0.19949**	-0.12711
	[0.54]	[-3.54]	[2.01]	[-0.85]
classmapp	-0.19615***	-1.41549***	0.09274	-0.54034***
	[-2.81]	[-4.15]	[0.84]	[-3.80]
classart	0.67115***	-0.70858***	0.15608	-0.43368*
	[6.83]	[-2.62]	[1.56]	[-1.84]
classvisual	0.28208***	-1.80990***	-0.10513	-0.92937***
	[3.80]	[-4.23]	[-0.91]	[-4.33]
male	0.03707	0.29518***	0.23030***	0.08566
	[0.64]	[2.88]	[2.78]	[0.70]
age1	-0.33613***	0.0504	-0.2917	0.13722
	[-2.69]	[0.18]	[-1.33]	[0.44]

age2	-0.22670**	-0.04697	-0.1581	0.12815
	[-2.35]	[-0.25]	[-0.75]	[0.60]
age4	-0.0481	-0.32140**	0.07275	-0.11617
	[-0.73]	[-2.00]	[0.64]	[-0.70]
age5	0.26668**	0.07222	-0.29056*	0.08344
	[2.30]	[0.38]	[-1.83]	[0.42]
age6	0.19497	-0.24899	-0.19172	0.02817
	[1.19]	[-1.13]	[-0.66]	[0.10]
age7	-0.13285	-0.32949	0.03301	0.66727**
	[-0.68]	[-1.01]	[0.09]	[1.98]
black	-0.65583***	0.17326	0.15526	-0.63781**
	[-5.89]	[0.77]	[0.69]	[-2.18]
indian	-0.08612	0.17667	-0.53314	-0.67061
	[-0.40]	[0.62]	[-1.47]	[-0.75]
islander	-0.32619***	-0.50410**	-0.068	0.98288***
	[-2.60]	[-1.99]	[-0.27]	[2.91]
emppt	0.33437***	-0.18437	0.02297	-0.35238
	[4.58]	[-1.03]	[0.14]	[-1.53]
unemp	0.21765	-0.03507	-0.54847***	-0.10862
	[1.56]	[-0.12]	[-2.99]	[-0.39]
retired	0.07865	0.32370**	-0.03546	0.29978
	[0.58]	[2.03]	[-0.21]	[1.41]
notforce	0.15014	0.07956	-0.03025	0.07003
	[1.46]	[0.42]	[-0.21]	[0.35]
widowed	0.05777	0.55029***	0.35349	-0.16089
	[0.45]	[2.90]	[1.31]	[-0.65]
single	0.47284***	0.48366***	0.21623	-0.32817
	[4.07]	[2.58]	[1.34]	[-1.40]
divorced	0.15017	0.42858**	0.33001**	-0.23132
	[1.62]	[2.50]	[2.13]	[-1.21]
hhldsize	-0.06309**	0.06188	-0.11735***	0.07086
	[-2.10]	[1.09]	[-3.05]	[1.44]
inc2	-0.24141*	-0.64223***	0.01689	-0.43365**
	[-1.82]	[-3.73]	[0.09]	[-2.15]
inc3	-0.08567	-0.70878***	0.0491	-0.40738**
	[-0.69]	[-3.26]	[0.23]	[-2.13]
inc4	0.06238	-1.20161***	-0.13275	-1.11099***
	[0.45]	[-5.32]	[-0.65]	[-5.15]
central	0.48904***	-0.05869	0.65396***	-0.47723**
balance	[5.46]	[-0.28]	[2.99]	[-1.99]
	0.05394	-0.06203	0.35045***	-0.06862
constant	[0.91]	[-0.55]	[3.79]	[-0.58]
	-0.317	1.13728***	-0.54328	2.34797***
	[-1.64]	[3.91]	[-1.23]	[7.04]
lnalpha	0.65087***		1.11074***	
	[23.44]		[5.05]	
N	16702		16702	
BIC	33.319.757		16.205.623	
AIC	32.647.832		15.533.697	

Dependent variables in count equations:

Number of jazz concerts or visits to museums and art galleries in the previous year among goers.

Dependent variables in inflation equation:

Latent dummy variable distinguishing "true" non-attendants and "goers".

Baseline categories: edu2 (high school), fatheredu2 (father graduated from high school), motheredu2 (mother graduated from high school), no art classes (for music, music appreciation, or arts), female, age3, white, full-time employed, married, inc1 (family annual income less than US$ 24,999), MSA status: metropolitan area, (controlling also for fatheredu99, motheredu99, inc99, and otherh).

4. Prediction accuracy of the models

In this section, we evaluate the predictive (in-sample) and forecasting (out-of-sample) accuracy of the estimated models using bootstrapping techniques to compute the predictive accuracy by the Brier score. This statistic, as proposed by Brier (1950), is the average deviation between predicted probabilities for a set of events and their outcomes; thus, a lower score represents higher accuracy.[4] Therefore, the Brier score is a measure of the accuracy of a set of probability assessments. The Brier score is defined as

$$B = \frac{\sum_{i=1}^{N} \left(P_i - X_i\right)^2}{N},$$

where P is the predicted probability of a given event, X takes the value of one if this event takes place and zero if it does not happen, and N is the number of forecasting instances, that is, individuals in the sample in our case. The Brier score takes the maximum value of one (with a systematically erroneous 0/1 forecast) and the minimum value of zero (when forecasts are also deterministic but always correct). Smaller values of the Brier score indicate more accurate predictions. Because our dependent variables are not defined in terms of binary events, we have classified people into four groups depending on the number of times that they have attended a jazz concert or visited an art museum or gallery in the previous year: non-attendants (never), moderate attendees (1-4 times), frequent attendees (5-10 times) and enthusiasts (over 10 times). Using the estimated models, we can then compute the expected membership probability for each group for all the individuals and compare it with the actual outcome, thus computing four different Brier scores. Moreover, when dealing with relatively improbable events (those with a probability below 0.5), such as attending a museum or a live jazz performance, the unconditional probability of this event can be thought as the baseline for B. If we make a prediction assigning a probability of one to the most likely outcome (not attending) and zero otherwise, the Brier score will be equal to the average probability of the event. Therefore, if we obtain a higher Brier score, the forecasting power of the model is poorer than just assigning a zero probability of attending a museum or a live jazz performance to the entire sample, and we can omit the model.

In each trial of the bootstrapping procedure, we randomly selected 25% of the sample to estimate the models presented in the previous section. We subsequently calculated the Brier scores for the four groups using that particular estimation sample, and we also assess the Brier scores for the remaining 75% of data and repeat this

[4] For the properties of the Brier score for evaluating probabilities see, for instance, Winkler et al. (1996). Lessmann (2012) employ the Brier score as an indicator of forecasting accuracy in competitive events. An application on the predictive power of count data in a different field can be found in Czado et al. (2009).

procedure 15,000 times. As a result, we obtained a distribution of Brier scores in-sample and out-of-sample for both dependent variables.

In general terms, the Brier scores are relatively small, being a first insight of the forecasting power of the estimated models. However, some relevant outcomes can be derived from Table 3. First, despite the group or the activity considered, in-sample values are slightly smaller than out-of-sample scores, but the means remain significantly different.[5] However, mean differences in relative terms are below 3.5% in all cases.

Second, because what we have called the baselines, that is, the unconditional probabilities of being in each of the four categories, are greater for visits to museums and galleries, the Brier scores appraised for this activity are larger than for jazz concerts both in and out-of-sample. In other words, because there is more variance regarding museum attendance, accurate forecasts are more difficult for this activity, and this is captured by a larger Brier score. Third, differences between the Brier scores and the baselines are larger for art museums and gallery visits; that is, estimated models can help us to a larger extent to enhance our knowledge about the expected behaviour for those activities with a larger variability among the population. Moreover, these differences with the baseline are larger for the first two groups, which are also the broadest groups. Fourth, the Brier score is always below the baseline, even for the smallest groups (frequent attendees and enthusiasts), for which predictions could be biased by the influence of the more numerous categories (non-attendants and moderate attendants).

Table 4
Bootstrapped Brier scores

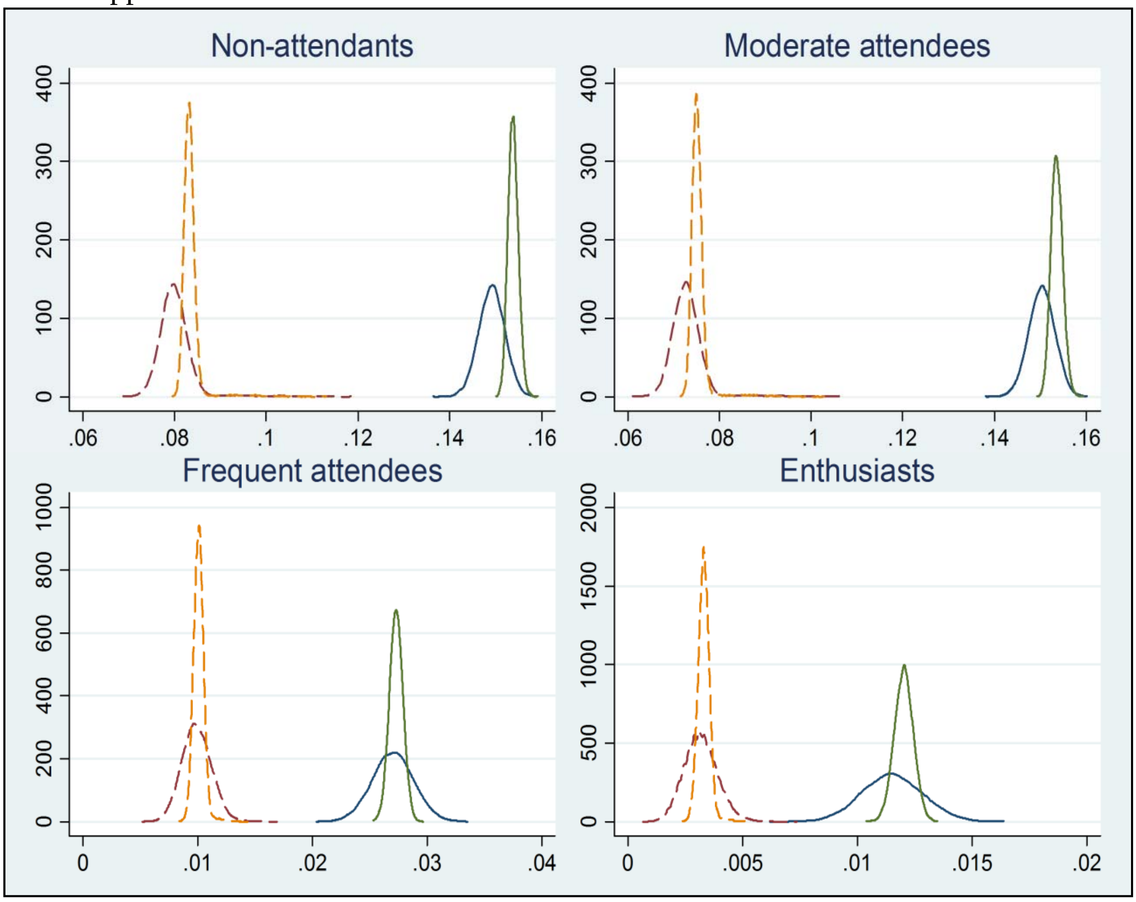
		Art museum & galleries			Jazz concerts		
		Mean	Std. Dev.	Baseline	Mean	Std. Dev.	Baseline
Non-attendants	In-sample	0.1491	0.0028	0.2689	0.0802	0.0040	0.1029
	Out-of-sample	0.1538	0.0011	0.2689	0.0835	0.0023	0.1029
Moderate attendees	In-sample	0.1503	0.0028	0.2267	0.0730	0.0039	0.0895
	Out-of-sample	0.1536	0.0013	0.2267	0.0754	0.0021	0.0895
Frequent attendees	In-sample	0.0270	0.0018	0.0296	0.0099	0.0013	0.0102
	Out-of-sample	0.0273	0.0006	0.0296	0.0101	0.0005	0.0102
Enthusiasts	In-sample	0.0115	0.0013	0.0126	0.0032	0.0007	0.0033
	Out-of-sample	0.0120	0.0004	0.0126	0.0033	0.0003	0.0033

[5] We have computed the t-test for the eight pairs of values, and in all cases, the mean differences are significant.

In Figure 1, we show the kernel densities of the bootstrapped Brier scores for the four alternative groups of attendees and both activities. As stated above, it is clear from these figures that the average out-of-sample Brier scores are larger than the in-sample means. However, the out-of-sample Brier scores lie usually within the confidence intervals of the in-sample Brier scores in almost all cases; assuming normality, more than 95% of the assessed out-of-sample values of the score lie within the 95% confidence interval of the corresponding in-sample Brier score, with the only exception being the non-attendants for museums, whose percentage is only 77%. Therefore, the out-of-sample and in-sample degrees of forecasting power of these models are so similar that the Brier scores evaluated out-of-sample cannot be rejected as being part of the in-sample distribution, although bootstrapped means are significantly larger.

Figure 1

Bootstrapped Brier scores



5. Discussion and conclusions

In this paper, we assessed the forecasting properties of the latent class count regression models for arts participation. The assessment of how well those behavioural models perform adds to the economic literature of cultural participation, and, further, this finding is also useful for decision makers and arts managers involved in marketing decisions.

After estimation, the in-sample and out-of-sample accuracies of the models were evaluated. Specifically, we verified the out-of-sample forecasting accuracy using bootstrapping techniques. In each trial, we estimated the jazz and museum attendance models by randomly sampling 25% of the original sample. We subsequently calculated the Brier scores for the other 75% of the sample. The results demonstrated that the predictions work well out-of-sample, as evidenced by the fact that out-of-sample Brier scores lie usually within the confidence intervals of the in-sample Brier scores in almost all cases. Therefore, we can rely on the forecasting accuracy of the estimated models and used them to extrapolate the behaviour of in-sample individuals to individuals not surveyed. This can be considered as a necessary condition for using the information given by econometric models as a basis of cultural policy.

Additionally, when comparing different activities, we have found that estimated models can help us to a larger extent to enhance our knowledge about the expected behaviour for those activities with a larger variability among the population, which in our case are visits to art museums and galleries. Obviously, additional information is especially valuable in these cases, as a larger variance makes it more difficult to establish any audience policy. Moreover, within activities, the estimated models imply a better knowledge that is larger for non-attendants and moderate attendees. These two groups are especially relevant, as they are the broadest categories and thus should be considered to be the most important targets of any cultural policy.

We have thus demonstrated that behavioural models are valid instruments to forecast cultural attendance. They allow improvements in the quality of the information available for scholars, policy makers and arts managers, which may contribute to improving the targeting of audiences and lead to more the efficient programming and promotion of cultural activities.

References

Andreasen, A. R., & Belk, R. W. (1980). Predictors of attendance at the performing arts. *Journal of Consumer Research, 7*(2), 112-120.

Ateca-Amestoy, V. (2008). Determining heterogeneous behavior for theater attendance. *Journal of Cultural Economics, 32*(2), 127-151, doi:10.1007/s10824-008-9065-z.

Borgonovi, F. (2004). Performing arts attendance: an economic approach. *Applied Economics, 36*(17), 1871-1885, doi:10.1080/0003684042000264010.

Brier, G. W. (1950). Verification of forecasts expressed in terms of probabilities. *Monthly Weather Review*, *78*(1), 1-3.

Bureau of the Census (Ed.). (2003). *Current Population Survey, August 2002: Public Participation in the Arts Supplement. Technical Documentation Attachments*. Washington: Realized by the Bureau of the Census for the National Endowment for the Arts.

Czado, C., Gneiting, T., & Held, L. (2009). Predictive Model Assessment for Count Data. *Biometrics*, *65*(4), 1254-1261, doi:10.1111/j.1541-0420.2009.01191.x.

Fernandez-Blanco, V., Orea, L., & Prieto-Rodriguez, J. (2009). Analyzing consumers heterogeneity and self-reported tastes: an approach consistent with the consumer's decision making process. *Journal of Economic Psychology, 30*(4), 622-633, doi:10.1016/j.joep.2009.04.005.

Gray, C. M. (2003). Participation. In R. Towse (Ed.), *A handbook of cultural economics* (pp. 356-365). Cheltenham, UK and Northampton, MA, USA: Edward Elgar.

Holbrook, M. B., & Schindler, R. M. (1994). Age, sex, and attitude toward the past as predictors of consumers' aesthetic tastes for cultural products. *Journal of Marketing Research, 31*(3), 412-422.

Jones, D. F., Collins, A., & Hand, C. (2007). A classification model based on goal programming with non-standard preference functions with application to the prediction of cinema-going behaviour. *European Journal of Operational Research*, *177*(1), 515-524, doi:10.1016/j.ejor.2005.11.014.

Lessmann, S., Sung, M-C., Johnson, J. E. V., & Ma, T. (2012). A new methodology for generating and combining statistical forecasting models to enhance competitive event prediction. *European Journal of Operational Research, 218*(1), 163-174, doi:10.1016/j.ejor.2011.10.032.

McCarthy, K. F., Ondaatje, E. H., & Zakaras, L. (2001). *Guide to the literature on participation in the arts*. Santa Monica, California: RAND Corporation.

National Endowment for the Arts (1981). *Audience development: an examination of selected analysis and prediction techniques applied to symphony and theater attendance in four southern cities* (Vol. Research Division Report # 14): National Endowment for the Arts.

National Endowment for the Arts (2004). *2002 Survey of public participation in the arts* (Vol. Research Division Report # 45): National Endowment for the Arts.

National Endowment for the Arts (2010). *2008 Survey of public participation in the arts* (Vol. Research Division Report # 49): National Endowment for the Arts.

Prieto-Rodriguez, J., Romero-Jordan, D., & Sanz-Sanz, J. F. (2005). Is a tax cut on cultural goods consumption actually desirable? A microsimulation analysis applied to Spain. *Fiscal Studies, 26*(4), 549-575, doi:10.1111/j.1475-5890.2005.00023.x.

Putler, D. S., & Lele, S. (2003). An easily implemented framework for forecasting ticket sales to performing arts events. *Marketing Letters, 14*(4), 307-320, doi:10.1023/B:MARK.0000012474.56171.e9.

Seaman, B. A. (2005). Attendance and public participation in the performing arts: a review of the empirical literature. *Nonprofit Studies Program, Georgia State University, Working Paper 05-03*.

UNESCO Institute for Statistics (2009). UNESCO Framework for Cultural Statistics. Institute for Statistics of the United Nations Educational, Scientific and Cultural Organization.

Weinberg, C. B. (1986). Arts plan: implementation, evolution, and usage. *MARKETING SCIENCE*, *5*(2), 143-158, doi:10.1287/mksc.5.2.143.

Weinberg, C. B., & Shachmut, K. M. (1978). Arts plan: a model based system for use in planning a performing arts series. *MANAGEMENT SCIENCE, 24*(6), 654-664, doi:10.1287/mnsc.24.6.654.

Winkler, R., Muñoz, J., Cervera, J., Bernardo, J., Blattenberger, G., Kadane, J., et al. (1996). Scoring rules and the evaluation of probabilities. *TEST*, *5*(1), 1-60, doi:10.1007/bf02562681.

Appendix:

Table A1. Variables used for the analysis and descriptive statistics

Variables	*Definition*	*mean proportion*	*st. error*
	Dependent variables		
Jazztime	number of jazz concerts in previous year	0.2973	16.316
Mustime	number of visits to museums and art galleries in previous year.	0.9218	46.384
	Cultural capital variables		
edu1	less than high school	0.1478	0.3549
edu3	college but not bachelors	0.2772	0.4476
edu4	bachelor	0.1691	0.3749
edu5	higher than bachelors	0.0871	0.282
fatheredu1	father: less than high school	0.4612	0.4985
fatheredu3	father: college but not bachelors	0.0865	0.2811
fatheredu4	father: bachelors	0.0930	0.2904
fatheredu5	father: higher than bachelors	0.0591	0.2358
fatheredu99	father: education missing	0.1927	0.3944
motheredu1	mother: less than high school	0.4111	0.492
motheredu3	mother: college but not bachelors	0.1065	0.3084
motheredu4	mother: bachelors	0.0830	0.2759
motheredu5	mother: higher than bachelors	0.0322	0.1764
motheredu99	mother: education missing	0.1638	0.3701
classmusic	has received music classes	0.3509	0.4773
classmapp	has received music appreciation classes	0.1581	0.3649
classart	has received art classes	0.1794	0.3837
classvisual	has received visual classes	0.1670	0.373
	Demographic variables		
male	male	0.4481	0.4973
age1	18-24	0.0975	0.2966
age2	25-34	0.1793	0.3836
age4	45-54	0.1923	0.3941
age5	55-64	0.1326	0.3391
age6	65-74	0.0986	0.2981
age7	75+	0.0868	0.2815
black	black	0.0907	0.2872
indian	American Indian, Aleut, Eskimo	0.0113	0.1055
islander	Asian or Pacific Islander	0.0385	0.1924
emppt	working part-time	0.1053	0.3069
unemp	unemployed	0.0333	0.1794
retired	retired	0.2331	0.4228
notforce	not in labour force	0.0950	0.2932
widowed	widowed	0.0808	0.2725
	Household variables		
hhldsize	household size	2.7963	14.829
divorced	divorced/separated	0.1355	0.3423
inc2	family annual income (25,000-39,999)	0.1805	0.3846
inc3	family annual income (40,000-74,999)	0.2616	0.4395
inc4	family annual income (75,000+)	0.2075	0.4055
inc99	income missing	0.1004	0.3006
	Habitat variables		
central	MSA status: central city	0.2170	0.4122
balance	MSA status: balance	0.3611	0.4803
otherh	MSA status: not identified	0.1675	0.3734