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Participation in cultural activities: specification issues

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Abstract In this paper, we analyse the frequency of individual attendance at cultural events comparing two econometric specifications—the zero-inflated negative binomial (ZINB) count data model and the double-hurdle model. Moreover, we address in detail the effect of education and economic variables—hourly earnings and non-labour income-on cultural demand. We use the Spanish Time Use Survey (*Encuesta de Empleo del Tiempo*) 2002–2003 and focus on working-age adults, running separate estimates by gender. Our results confirm that the ZINB model is more suitable to our data than the double-hurdle one. We also conclude that education and income-related variables are important determinants of both the probability of participating and the frequency of participation.

Keywords Cultural participation · Zero-inflated negative binomial model · Cragg model

JEL Classification Z1 · C52

1 Introduction

The objective of this paper was to analyse the determinants of the frequency of participation in cultural activities, measured as the number of times the individual has attended cultural events in the past 4 weeks. Our purpose is double. First, we compare two alternative econometric specifications: the zero-inflated negative binomial (ZINB) count data model and the double-hurdle model with independent errors (Cragg model). Second, we contribute to the debate about the relevance of

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education and economic factors as determinants of cultural demand performing several alternative estimates and computing the marginal effects of these variables.

There is wide empirical literature on cultural consumption such as theatre attendance (e.g. Ateca-Amestoy 2008; Swanson et al. 2008; Castiglione 2011; Zieba 2011; Grisolía and Willis 2011), music (e.g. Kurabayashi and Ito 1992; Prieto-Rodríguez and Fernández-Blanco 2000; Favaro and Frateschi 2007), cinema (e.g. Fernández-Blanco and Baños-Pino 1997; Dewenter and Westermann 2005; Fernández-Blanco et al. 2009) or museum attendance (e.g. DiMaggio 1996; Frey and Meier 2006; Brida et al. 2012, 2014).

We have adopted a broad definition of cultural events including attendance at theatre plays, dance, concerts, cinema, and visits to museums and monuments. Our definition includes both highbrow and popular arts, because the survey does not distinguish between them. Moreover, all activities considered have in common that they take place outside home. The main reason to choose this definition is that we are interested in analysing the determinants of cultural participation in general, and this issue may also be relevant for authorities whose aim was to promote any kind of cultural demand as a way to achieve social development and cohesion.[1]

The participation decisions are usually modelled as probit or logit regression models (e.g. Favaro and Frateschi 2007; Hand 2009; Wen and Cheng 2013). The intensity of participation has been modelled through OLS (e.g. Bihagen and Katz-Gerro 2000), Tobit and Heckman specifications (e.g. Lévy-Garboua and Montmarquette 1996), ordered probit or logit models (e.g. Borgonovi 2004; Castiglione 2011; Falk and Falk 2011; Masters et al. 2011), finite mixture models (e.g. Castiglione 2011) or count data models (e.g. Ateca-Amestoy 2008, 2010; Ateca-Amestoy and Prieto-Rodríguez 2013; Brida et al. 2012, 2014; Wen and Cheng 2013; Muñiz et al. 2014).

One of the characteristics of individual data on cultural demand is that there is a high proportion of population who has not participated in cultural activities during the studied period. The lack of participation may be due to several reasons such as tastes, monetary or budget constraints. The presence of zeros should be taken into account when choosing the statistical techniques to analyse individual behaviour regarding cultural activities. This is the main reason to choose the two econometric specifications applied in this paper: ZINB and Cragg models. Both of them explicitly model non-participation assuming that it may be explained by two reasons: deliberate abstentions or potential consumers who have not participated in the activity during the time period considered. The main differences between both models are that count data models take into account that the dependent variable can only take integer values and assume a nonlinear relationship, whereas the dependent variable in double-hurdle models is continuous and is a linear function of the parameters.

The ZINB model has been applied by Ateca-Amestoy (2008, 2010) to study attendance at theatre and other cultural events, Ateca-Amestoy and Prieto-Rodríguez (2013) to analyse jazz concerts and visits to museums or galleries,

[1] Other papers that aggregate cultural activities are Bihagen and Katz-Gerro (2000), Alderighi and Lorenzini (2012) or Wen and Cheng (2013).

Montoro-Pons et al. (2013) for popular musical audience, Wen and Cheng (2013) to explain performing arts attendance, and Muñiz et al. (2014) to cultural events attendance. Regarding double-hurdle methodology, as far as we know, it has only been applied by Brida et al. (2013) to individual expenditures on visits to museums. However, this model has not been used to explain participation in cultural events yet.[2]

This paper is an extension of Muñiz et al. (2014), where the authors analyse cultural and sports frequency of participation and compare different count data models using the same database, concluding that the ZINB model is the one that best suits the data. Now, we take a step further by comparing the ZINB and the double-hurdle models. To the best of our knowledge, this is the first study that compares these models to study cultural events attendance, and it is also the first time that the double-hurdle specification is applied to cultural participation.

Apart from econometric modelling, another relevant specification issue refers to the vector of covariates. In particular, an important topic in cultural economics literature is the influence of income and education, two variables that are usually considered as important determinants of individual's participation in cultural events. Seaman (2005, 2006) discusses this issue in detail, focusing on the economics of highbrow culture. This author notes that, although theoretical analysis assumes that education is a key variable in performing arts demand, many empirical models do not confirm this result. Some empirical studies obtain a weak impact of formal education in demand models when controlling for other determinants such as income, and others find econometric evidence favouring specific forms of arts training over individual's formal education.

The second goal of our paper was to further analyse the effect of education and income on attendance at cultural events. We elaborate on this issue by including as covariates the educational level and two economic variables: hourly earnings and non-labour income. Since education is an important determinant of labour earnings, so there may be multicollinearity problems, we try different estimates that vary in function of the covariates included: education and earnings, only education, and only earnings. In addition, we compute the marginal effects of all these variables—elasticities in the case of economic variables—from the final estimates.

In our empirical analysis, we use the 2002–2003 Spanish Time Use Survey. We estimate individual attendance at cultural events separately for men and women because, even though there have been advances in gender equality in the developed societies, gender differences in the distribution of time persist nowadays.[3] Previous studies have generally found differences between males and females in cultural participation, but usually they do not separate the sample by gender, but they include it as a dummy covariate. Our approach is more flexible since it allows socio-demographic and economic variables to have a different effect on males and females behaviour.

[2] However, it has been used in other fields such as sports economics. For example, Buraimo et al. (2010) estimate double-hurdle models to explain the number of days that individuals have practiced sports within a four-week period.

[3] See, e.g. Sayer (2005) and Giménez-Nadal and Sevilla (2012).

Our main conclusions are that the ZINB model is more appropriate for our data than the double-hurdle one, and that both education and income are relevant and increase the likelihood and the frequency of participation in cultural activities. Furthermore, there are differences in the influence of the covariates on the frequency and on the participation decisions. Finally, we also find that male and female responses to changes in some explanatory variables differ.

The rest of the paper proceeds as follows. In Sect. 2, we discuss the database and the variables used in our empirical estimates. Section 3 specifies the two econometric methodologies applied in our paper. In Sect. 4, we present and comment on the estimation results. In Sect. 5, we summarise the main contributions of our study.

2 Data and variables

The database used in this paper is the Spanish Time Use Survey conducted by the Spanish Statistical Office (*INE*) in 2002–2003. This survey gathers data on some 60,000 individuals aged 10 or older from around 24,000 households. The data collection was carried out between October 2002 and September 2003 homogeneously over the four quarters. It contains information about personal and family characteristics, individual time allocation along a specific day, as well as recent participation in sports, cultural or other leisure activities.

Although there is a more recent wave of this survey conducted in 2009–2010, the questions related to participation in cultural activities have been removed in the second wave so that we could not use it.

The dependent variable in our models is defined as the number of times the individual has attended cultural events during the previous 4 weeks. Specifically, the cultural events considered are theatre, ballet and classical dance, cinema, concerts, as well as visits to museums and monuments.

The selected sample is composed of working-age adults. We selected this age group because their time allocation decisions probably differ from other groups such as young or retired people, and because we include earnings as an explanatory variable. In addition, other filters are introduced in the sample in order to generate all the variables used in the estimations.

Table 1 shows the distribution of the dependent variable for both males and females.

The first thing to notice is that there are not relevant differences by gender. Secondly, our database displays a large number of zeros in the dependent variable. Looking at the information, around 60 % of females and males did not engage in cultural events along the period. This characteristic will be taken into account in the empirical specification. Thirdly, as expected, the distributions are skewed to the left, i.e. the sample is concentrated on small values of frequency of attendance and the number of individuals who attended cultural events tends to decrease as frequency increases. Finally, another characteristic of our dependent variables is that there are some individuals with high frequencies, although this information does not appear

Table 1 Frequency of attendance at cultural events

Frequency	Males		Females	
	#	%	#	%
0	7479	60.68	8933	60.96
1	1516	12.30	1867	12.74
2	1298	10.53	1483	10.12
3	593	4.81	732	4.99
4	583	4.73	600	4.09
5	228	1.85	309	2.11
6	202	1.64	273	1.86
7	95	0.77	128	0.87
8	92	0.75	90	0.61
9	44	0.36	41	0.28
10	63	0.51	50	0.34
11	14	0.11	25	0.17
12	19	0.15	20	0.14
13	18	0.15	22	0.15
14	15	0.12	15	0.10
15	12	0.10	12	0.08
>15	54	0.44	55	0.38
Total	12,325	100.00	14,655	100.00

in the table because all values over 15 have been grouped. The variable reaches a maximum of 55 times in the case of women and 50 in the case of men.

Regarding the covariates included, we assume that the individual frequency of participation in cultural events depends on personal and family characteristics that determine preferences. Moreover, non-labour income and wage are included to reflect the budget constraint the individual faces, as well as other variables to control for the supply of cultural activities. Specifically, the explanatory variables included in our analysis are age (and its squared), marital status, number of children younger than 13, a dummy about the number of adults at home, educational-level dummies, non-labour income (defined as family net income excluding individual earnings), logarithm of hourly earnings, labour status (a dummy variable equal to one if the individual is working), term dummies, and degree of urbanisation.

Since we do not know the earnings of non-workers, we estimate a wage equation with the subsample of workers—applying the Heckman selection model to take into account the sample selection bias. From the estimated coefficients, predicted earnings are computed for non-workers conditioned on their labour status, whereas for workers we use their observed wages.[4]

Tables 8 and 9 in the "Appendix" include the definition of all the variables used as well as their descriptive statistics by gender. In general, there are no major differences between males and females in the mean values of the covariates. The

[4] See García (1991) for a discussion about alternative methodologies to predict wages.

only exceptions are the labour status, wage and non-labour income. The proportion of working men almost doubles that of women, and the average wage is considerably higher for men than for women, unlike non-labour income.

3 Econometric specifications: ZINB and double-hurdle models

The dependent variables in our research record the number of times that a particular event takes place in a time interval. As seen in the previous section, one of the characteristics of our data is the high percentage of individuals who have not attended cultural events in the period. There may be two main reasons to explain lack of participation. First, there are people who are not interested in those activities and they would never participate. Second, there are individuals who may be interested in them, but they have not participated during that period. In this section, we present two econometric models to analyse individual participation in cultural activities: the zero-inflated negative binomial count data model and the double-hurdle model. Both of them allow for both types of non-participation.

Count data specifications are nonlinear discrete-choice models, estimated by maximum likelihood, which assume that the dependent variable can only take non-negative integer values. In the count data literature, various distributions have been proposed for the dependent variable.[5] Muñiz et al. (2014), using similar data, confirm that the ZINB model is the specification that best fits the data.

The ZINB model considers two types of subpopulations, usually named the Always-Zero group and Not-Always-Zero group.[6] The Always-Zero group is composed of all those individuals who never would take part in the activity. On the contrary, the Not-Always-Zero group includes potential participants, i.e. people who may or not participate depending on the restrictions they face. It is worth noting that our survey does not differentiate between both types of non-participation.

The ZINB model assumes that the probability that an individual belongs to the Always-Zero group follows a logit specification:

$$\psi_i = p(A_i = 1|z_i) = \frac{\exp(z_i\gamma)}{1 + \exp(z_i\gamma)} \tag{1}$$

In Eq. (1), A_i is a binary variable that is equal to one if the individual belongs to the group and zero otherwise; z_i is the vector of explanatory variables; and γ is the vector of parameters to be estimated.

Regarding the individuals with positive levels of participation or zero participation due to corner solutions (the Not-Always-Zero group), the probability of each count is computed by a negative binomial regression:

[5] See Cameron and Trivedi (2013) for a comprehensive analysis of count data models.

[6] In the reminder of this section, we detail the econometric specification of the ZINB model, following Long and Freese (2006).

$$p(Y = y_i|x_i) = \frac{\Gamma(y_i + \alpha^{-1})}{y_i!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i} \tag{2}$$

In the previous equation, Y is a discrete variable that records the number of times the individuals have attended cultural events over the past 4 weeks, Γ is the gamma function, α is a parameter to be estimated, and μ_i is the expected number of counts for the Not-Always-Zero group and it is specified as:

$$\mu_i = \exp(x_i\beta) \tag{3}$$

where β is a vector of coefficients, and x_i is a vector of covariates.

Exclusion restrictions are not required for identification. Therefore, the vectors of explanatory variables z_i and x_i may contain the same covariates. In fact, we include the same variables in both parts of the model.

According to the above assumptions, the log-likelihood function of the ZINB specification is:

$$\begin{aligned}\log L = &\sum_{\{y_i=0\}} \log\left[\psi_i + (1 - \psi_i) * \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}}\right] \\ &+ \sum_{\{y_i>0\}} \left[\log(1 - \psi_i) + \log\Gamma\left(y_i + \alpha^{-1}\right) + \log\Gamma(y_i + 1) - \log\Gamma\left(\alpha^{-1}\right)\right. \\ &\left.+ \alpha^{-1}\log\left(\alpha^{-1}\right) + y_i\log(\mu_i) - (\alpha^{-1} + y_i)\log(\alpha^{-1} + \mu_i)\right]\end{aligned} \tag{4}$$

Our dependent variables only take zero or positive integer values, so that the ZINB count data model might seem the most appropriate specification a priori. However, they take high values for some individuals, and therefore, they could also be treated as continuous, in which case the double-hurdle specification can be applied.

On that basis, we consider that it is interesting to compare both methodologies with our database. Although both models have been previously applied in the cultural economics literature, to our knowledge double-hurdle models have not been applied to the analysis of the frequency of participation in cultural activities.

The double-hurdle models are so called because individuals must overcome two hurdles to observe a positive value in participation. First, the individual decides whether or not to participate. Second, those who opt for demanding the activity have to choose how often to demand. Thus, the specification of this model consists of two equations:

$$y^*_{i1} = Az_i + u_i \tag{5}$$

$$y^*_{i2} = Bx_i + v_i \tag{6}$$

where y^*_{i1} is a latent index that determines whether the individual i participates ($y_{i1} = 1$) or not ($y_{i1} = 0$) in cultural activities; y^*_{i2} is a latent variable representing how many times the individual has participated in cultural activities in the previous

4 weeks; z_i is a vector of covariates that explains the participation decision; and x_i is a vector of independent factors affecting the frequency decision. Moreover, A and B are vectors of parameters. Finally, u_i and v_i are unobserved random variables that follow a normal distribution.

Equation (5) is the first hurdle representing the participation decision, and Eq. (6) is the second hurdle, which specifies the subsequent individual decision about frequency. The observed dependent variable, y_i, can be positive or zero—in the case that the individual is not a potential participant ($y^*_{i1} \leq 0$) or he might participate ($y^*_{i1} > 0$), but he has not done it along the period ($y^*_{i1} > 0$, $y^*_{i2} \leq 0$).

$$\begin{cases} y_i = Bx_i + v_i \quad if\, y^*_{i1} > 0 \quad \text{and } y^*_{i2} > 0 \\ y_i = 0 \quad \text{otherwise} \end{cases} \tag{7}$$

In our empirical specification, we have assumed that there is independence between the error terms in the participation and frequency equations. Therefore, we estimate a double-hurdle model with independent errors, also called Cragg model because this author was the first one to propose it (Cragg 1971).[7]

The likelihood function for the Cragg model is:

$$L = \prod_1 P(v_i > -Az_i)P(u_i > -Bx_i)f(y_i|u_i > -Bx_i)* \tag{8}$$

$$\prod_0 (1 - P(v_i > -Az_i)P(u_i > -Bx_i))$$

In Eq. (8), we use the subscript 0 to denote those individuals whose level of frequency for cultural activities is zero and a subscript 1 for all other individuals, whose intensity level for cultural activities is positive. Then, $\prod_0$ is the product operator for observations where $y_i = 0$, and $\prod_1$ is the product operator for observations where $y_i > 0$. Finally, f is the probability density function for a standard normal random variable.

Double-hurdle models have a flexible structure and do not require exclusion restrictions to identify the equations. Therefore, the same explanatory variables are included in both the participation and the frequency equations, as we did in the ZINB specification.

4 Analysis of empirical results

In this section, we first compare double-hurdle versus ZINB estimates, and secondly, we comment the main results of our final specification, focusing on the effect of education and economic variables on cultural event attendance.

[7] We tried to estimate a double-hurdle model allowing for correlation between the disturbance terms, but we did not achieve convergence.

4.1 ZINB model versus double-hurdle model

Table 2 shows the coefficients and *t* statistics for both the ZINB and the double-hurdle models. The coefficients are not directly comparable because the ZINB model is a nonlinear specification, and in addition, the participation decision is modelled in a different way: the ZINB model specifies the probability of belonging to the Always-Zero group, whereas the double-hurdle model specifies the probability of being a potential participant. This is the reason why the coefficients in the participation equations are generally of opposite sign.

In general, the set of significant covariates in the participation equations is the same in both specifications and have the same qualitative effect. However, it is worth noting that in the double-hurdle model, no variable is significant in explaining frequency of attendance at cultural events.

Since count data and double-hurdle models are not nested, we compare them by using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The AIC is computed as:

$$\mathrm{AIC} = -2\mathrm{Log}L + 2k \tag{9}$$

where Log L is the maximised log-likelihood value and k is the number of parameters in the model.

The Bayesian information criterion (BIC) is:

$$\mathrm{BIC} = -2\mathrm{Log}L + (\mathrm{Log}N)k \tag{10}$$

where N is the number of observations.

The model with the smallest information criteria will be the preferred one. The values of these criteria are shown in Table 3 and allow us to conclude that the ZINB model is the one that best fits to our data.

After selecting the econometric specification, we turn now to the analysis of results. In first place, we discuss the inclusion of two explanatory variables: education and earnings. In second place, we present and comment on our final estimates.

4.2 ZINB count data estimates: education versus earnings

Previous models included wages and education as covariates, two variables that may cause a multicollinearity problem, given that education is a key determinant of individual productivity and thus of earnings.

To clarify the influence of these variables, we performed several ZINB count data estimates. In addition to the specification discussed in previous section, in which we included earnings and the educational level, we also estimate the models for both activities including wages but not education, and education but not wages. The remaining covariates are the same as in previous section. Table 4 includes the coefficients and *t*-values of the education dummies and the logarithm of hourly earnings, as well as the Akaike and Bayesian information criteria for the three sets

Table 2 Cultural event attendance: ZINB and double-hurdle models

Explanatory variables	ZINB				Double hurdle			
	Males		Females		Males		Females	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
	Frequency decision				*Frequency decision*			
Age	0.00300	0.27	−0.00225	−0.19	1.28541	0.90	0.09373	0.06
$Age^2/100$	0.00766	0.55	0.00947	0.65	−0.78458	−0.51	0.93922	0.47
Married	−0.31434	−4.22	−0.33198	−5.69	−16.85052	−1.48	−35.83893	−1.31
No. child. ≤12	−0.22254	−4.98	−0.24129	−6.36	−20.86974	−1.62	−28.59532	−1.30
Adult3	−0.08638	−1.93	−0.07705	−1.99	−5.39556	−1.01	−11.88392	−1.16
Educ. 1	0.06595	0.90	0.24251	3.41	34.1910	0.39	35.43076	1.24
Educ. 2	0.27862	3.82	0.39703	5.38	21.51120	1.44	57.56031	1.30
Educ. 3	0.57647	6.85	0.52126	6.43	50.00067	1.67	67.26864	1.31
Worker	−0.02598	−0.53	−0.15802	−3.38	−7.57483	−1.15	−22.04277	−1.25
Log (wage)	−0.03960	−0.86	0.11959	2.69	−2.51013	−0.52	17.48542	1.20
Nlabinc	0.00009	4.62	0.00009	5.00	0.00627	1.57	0.01004	1.31
Quart. 1	−0.23284	−4.67	−0.08621	−1.92	−20.83909	−1.60	−12.68677	−1.10
Quart. 2	−0.13066	−2.56	−0.10096	−2.21	−10.17143	−1.29	−12.08784	−1.07
Quart. 3	−0.01111	−0.19	0.07517	1.39	−12.2300	−0.23	11.53558	1.06
Urb. 2	−0.08145	−1.15	−0.13689	−2.23	−34.6389	−0.45	−18.60507	−1.10
Urb. 3	−0.10165	−2.54	−0.08518	−2.30	−8.36155	−1.32	−11.33548	−1.15
	P(Always-Zero Group)				$P(y^*_1 > 0)$			
Age	0.27604	10.19	0.19279	7.88	−0.07873	−10.05	−0.05209	−7.55
$Age^2/100$	−0.23318	−7.81	−0.15720	−5.77	0.06390	6.82	0.03756	4.57
Married	0.29890	2.48	0.42327	4.10	−0.26885	−7.29	−0.31171	−10.21
No. child. ≤12	0.18655	2.52	0.23283	3.57	−0.16130	−7.34	−0.19559	−10.14

Table 2 continued

Explanatory variables	ZINB				Double hurdle			
	Males		Females		Males		Females	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Adult3	0.27492	3.16	0.21741	2.86	−0.14098	−4.81	−0.09883	−3.82
Educ. 1	−0.66078	−6.38	−0.62044	−7.05	0.32810	8.74	0.37217	11.31
Educ. 2	−1.30426	−11.39	−1.19316	−10.05	0.66933	16.80	0.65719	17.20
Educ. 3	−2.01124	−11.64	−1.96509	−9.74	0.96728	19.69	0.92530	19.59
Worker	−0.77947	−7.87	−0.24427	−2.58	0.28466	8.59	0.02353	0.80
Log (wage)	−0.73622	−7.73	−0.51496	−4.58	0.23792	8.15	0.22197	7.35
Nlabinc	−0.00034	−6.32	−0.00035	−7.23	0.00014	9.77	0.00015	11.58
Quart. 1	−0.12555	−1.18	−0.08375	−0.89	−0.05180	−1.48	0.00154	0.05
Quart. 2	0.14481	1.37	−0.04998	−0.52	−0.09993	−2.81	−0.03185	−1.00
Quart. 3	0.08340	0.76	0.11793	1.22	−0.04252	−1.15	−0.02646	−0.79
Urb. 2	0.15601	1.05	0.20992	1.58	−0.12268	−2.53	−0.11157	−2.56
Urb. 3	0.22591	2.67	0.31112	4.14	−0.15088	−5.60	−0.15003	−6.15

Table 3 Comparison between ZINB and double-hurdle models

	ZINB		Double hurdle	
	Males	Females	Males	Females
N	12,325	14,655	12,325	14,655
Log L	−16,100.63	−19,040.51	−17,012.77	−20,109.61
AIC	32,271.268	38,151.013	34,095.55	40,289.22
BIC	32,530.946	38,416.751	34,355.23	40,554.96

of estimates. The results for the rest of variables do not differ substantially amongst the different specifications.[8]

The first part of the table corresponds to the results regarding frequency of participation of the Not-Always-Zero group. The last part of the table provides information on the determinants influencing the probability of belonging to the Always-Zero group. Given that count data models are nonlinear, the interpretation of the coefficients is not straightforward, although their signs indicate whether the relationship is direct or inverse. If the coefficient has a positive sign in the inflated part of the model, the variable increases the probability of being a non-participant. Moreover, if the variable has a positive sign in the frequency part, it means that the variable has a positive effect on the expected number of counts.

As we show in the table above, the effects of earnings and education are similar when included in isolation: both factors significantly increase the probability of participating and the frequency of participation. Moreover, their significance level and their coefficients are in general higher than when both determinants are included simultaneously.

In our final estimates, wage and/or education covariates were dropped in those parts of the model where they were not significant. In this way, we partially overcome the problem of multicollinearity, and we keep those variables that seem to be most relevant for explaining individual decisions. The final models are compared to the complete specification—which includes earnings and education—and the former are always preferred.[9] Therefore, we removed individual earnings from the male frequency equation and keep both set of covariates in the female model.

Table 5 includes our definitive ZINB estimates for the number of times that males and females attended cultural events.

According to our results, age only affects participation: young and elderly people have a higher probability of participating. This result could be linked to the effects of the life cycle: family responsibilities that arise during middle age might reduce individuals' cultural participation (Gray 2003; Borgonovi 2004). In fact, the variables related to family composition (dummy variables capturing the number of adults in the household, the marital status and the number of children under 13) are significant and have the expected effect of increasing the likelihood of belonging to

[8] The full results of these estimates are available upon request.

[9] As the different specifications of ZINB are nested models, the LR test has also been applied to compare the various models. The results of the LR test also support the choice of our final model.

Table 4 ZINB estimates: wage *versus* education

Explanatory variables	Males		Females		Males		Females		Males		Females	
	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*	Coef.	*t*
Frequency												
Log (wage)	0.12866	3.24	0.23157	5.83					−0.03960	−0.86	0.11959	2.69
Educ. 1					0.05645	0.78	0.25092	3.55	0.06595	0.90	0.24251	3.41
Educ. 2					0.25657	3.59	0.42774	5.97	0.27862	3.82	0.39703	5.38
Educ. 3					0.54278	7.01	0.59458	7.94	0.57647	6.85	0.52126	6.43
P(A = 1)												
Log (wage)	−1.25285	−13.74	−1.32587	−11.15					−0.73622	−7.73	−0.51496	−4.58
Educ. 1					−0.73142	−7.21	−0.66297	−7.62	−0.66078	−6.38	−0.62044	−7.05
Educ. 2					−1.51776	−13.57	−1.36621	−12.10	−1.30426	−11.39	−1.19316	−10.05
Educ. 3					−2.49511	−14.96	−2.36187	−12.56	−2.01124	−11.64	−1.96509	−9.74
N	12,325		14,655		12,325		14,655		12,325		14,655	
Log L	−16,371.71		−19,251.78		−16,138.5		−19,070.56		−16,100.63		−19,040.51	
AIC	32,801.43		38,561.56		32,343.01		38,207.11		32,530.94		38,416.751	
BIC	33,016.59		38,781.75		32,587.85		38,457.66		32,271.26		38,151.013	

Other variables considered are age (and age squared), marital status, number of children younger than 13, a dummy about the number of adults, non-labour income, logarithm of hourly earnings, labour status, and dummies to control for the term and degree of urbanisation

Table 5 Cultural attendance: final ZINB estimates

Explanatory variables	Males		Females	
	Coef.	*t*	*Coef.*	*t*
Frequency				
Age	0.00176	0.16	−0.00225	−0.19
$Age^2/100$	0.00848	0.61	0.00947	0.65
Married	−0.31610	−4.25	−0.33198	−5.69
No. child. ≤12	−0.22436	−4.99	−0.24129	−6.36
Adult3	−0.08275	−1.87	−0.07705	−1.99
Educ. 1	0.06216	0.85	0.24251	3.41
Educ. 2	0.26867	3.74	0.39703	5.38
Educ. 3	0.55331	7.11	0.52126	6.43
Worker	−0.03256	−0.67	−0.15802	−3.38
Log (wage)			0.11959	2.69
Nlabinc	0.00009	4.58	0.00009	5.00
Quart. 1	−0.23351	−4.69	−0.08621	−1.92
Quart. 2	−0.13142	−2.57	−0.10096	−2.21
Quart. 3	−0.01117	−0.19	0.07517	1.39
Urb. 2	−0.08187	−1.16	−0.13689	−2.23
Urb. 3	−0.10087	−2.52	−0.08518	−2.30
P(A = 1)				
Age	0.27557	10.15	0.19279	7.88
$Age^2/100$	−0.23294	−7.79	−0.15720	−5.77
Married	0.29478	2.45	0.42327	4.10
No. child. ≤12	0.18482	2.49	0.23283	3.57
Adult3	0.27750	3.18	0.21741	2.86
Educ. 1	−0.66462	−6.42	−0.62044	−7.05
Educ. 2	−1.31517	−11.54	−1.19316	−10.05
Educ. 3	−2.03550	−11.99	−1.96509	−9.74
Worker	−0.78357	−7.92	−0.24427	−2.58
Log (wage)	−0.70197	−8.22	−0.51496	−4.58
Nlabinc	−0.00034	−6.31	−0.00035	−7.23
Quart. 1	−0.12773	−1.20	−0.08375	−0.89
Quart. 2	0.14314	1.36	−0.04998	−0.52
Quart. 3	0.08153	0.75	0.11793	1.22
Urb. 2	0.15557	1.04	0.20992	1.58
Urb. 3	0.22679	2.67	0.31112	4.14
N	12,325		14,655	
Log L	−16,101.16		−19,040.51	
AIC	32,270.31		38,151.01	
BIC	32,522.57		38,416.75	

the Always-Zero group and reducing the frequency of participation in cultural activities.

The influence of being working is interesting because workers are more likely to attend cultural events, but, in the case of women, they have a lower frequency of attendance than non-workers. In fact, this is the main difference between males and females: the labour status does not significantly affect male frequency of participation in cultural activities, but it reduces the frequency of attendance of working females. Another important difference is that labour earnings do not affect male frequency decisions, but increase female frequency of participation.

Some studies have analysed the relationship of temperature and weather on the allocation of leisure time and outdoor recreation (Zivin and Neidell 2014; Finger and Lehmann 2012). In addition to the impact of climatology, individuals are usually on holiday during the summer, and this may encourage leisure activities. Nevertheless, the participation often depends on the supply of activities. In our case, the quarter of the year is not significant for cultural participation, but the frequency of attendance at cultural events falls in the first half of the year. The lack of significance of the quarter of the year on the probability of belonging to the Always-Zero group could be explained because the factors that affect this probability are probably more related to variables regarding the formation of preferences than the time period in which the survey was conducted.

Regarding the geographical variables, the likelihood of never participating is greater in less populated areas. This is a sensible result since the presence of cultural facilities conditions the supply. Moreover, the frequency decreases outside provincial capitals. These findings corroborate previous results. Heilbrun and Gray (2001) note that live performing arts and museums are pre-eminently urban activities. Furthermore, Bille and Schulze (2006) indicate that most cultural institutions, such as symphony orchestras, ballet companies, and museums, tend to be located in large cities. All these institutions require a minimum size of market, and they are not generally viable below this threshold.

We turn now to the analysis of the effect of education and economic variables, which are amongst the variables with the highest degree of significance. The educational level has a direct positive effect on participation and frequency decisions, in addition to its indirect effect via hourly earnings. Non-labour income and earnings also have a positive effect on both the probability of belonging to the Not-Always-Zero group and on the frequency of participation in cultural activities.

To gain a better understanding of the importance of these covariates in explaining individual decisions about cultural activities, we have computed their marginal effects or the elasticities in the case of earnings and non-labour income. The marginal effects show how much the expected number of counts changes in response to a unit change in the explanatory variable.

To explain how we compute the marginal effects, we start by specifying the expected value of counts, which is equal to the product of the probability that the individual belongs to the Not-Always-Zero group ($A = 0$) and the expected value of counts in this group[10]:

[10] Individual subscripts are omitted for notational convenience.

$$E(y|x, z) = p(A = 1|z) * 0 + p(A = 0|x, z) * E(y|x, zA = 0) \\ = [\mu * (1 - \psi)] \tag{11}$$

where ψ is defined in Eq. (1) and μ in Eq. (3).

Thus, the marginal effect of x_k on the expected number of counts when x_k is a continuous covariate can be expressed as:

$$\frac{\partial E(y|x, z)}{\partial x_k} = \frac{\partial(1 - \psi)}{\partial x_k} * \mu + (1 - \psi) * \frac{\partial \mu}{\partial x_k} \tag{12}$$

As shown in the above equations, if x_k is included in both parts of the model, it influences the expected value of y in two ways: on the one hand, it modifies the probability of belonging to the Not-Always-Zero group, and on the other hand, it also affects the expected number of counts, conditioned to belonging to that group.

Besides the total marginal effect (Eq. 12), we will also show the two partial marginal effects, which can be expressed as[11]:

$$\frac{\partial p(A = 0|x_k)}{\partial x_k} = \frac{\partial(1 - \psi)}{\partial x_k} = -\gamma_k * \psi * (1 - \psi) \tag{13}$$

$$\frac{\partial E(y|x_k, A = 0)}{\partial x_k} = \frac{\partial \mu}{\partial x_k} = \beta_k * \exp(x\beta) \tag{14}$$

Since education is measured through the inclusion of three dummy variables, the total marginal effect is the difference between the expected value of the dependent variable when the dummy (*dj*) is equal to one and zero, respectively:

$$E\left(y|d_j = 1, x_k\right) - E\left(y|d_j = 0, x_k\right) = \left\{\left[(1 - \psi)|d_j = 1\right]E\left(y|d_j = 1, A = 0\right)\right\} \\ - \left\{\left[(1 - \psi)|d_j = 0\right]E(y|d_i = 0, A = 0)\right\} \tag{15}$$

Moreover, the partial effects of d_j on the probability of being a potential participant ($A = 0$), and on the expected number of counts in the Not-Always-Zero group are, respectively, equal to:

$$p\left(A = 0|d_j = 1\right) - p\left(A = 0|d_j = 0\right) = \left[(1 - \psi)|d_j = 1\right] - \left[(1 - \psi)|d_j = 0\right] \tag{16}$$

$$E\left(y|d_j = 1, A = 0\right) - E\left(y|d_j = 0, A = 0\right) = \left[\exp(x\beta)|d_j = 1\right] - \left[\exp(x\beta)|d_j = 0\right] \tag{17}$$

Table 6 reports the means and standard deviations of the total marginal effects, the marginal effects on the probability of being a potential participant, and the marginal effects on the expected number of counts, conditioned on being a potential participant. Finally, Table 7 contains information about the average earnings and non-labour income elasticities.

[11] McDonald and Moffitt (1980) define this decomposition of marginal effects for Tobit models.

Table 6 Marginal effects of education

	Total marginal effects		Marginal effects on the probability of being a potential participant		Marginal effects on the expected number of counts conditioned on $A_i = 0$	
	Mean	SD	Mean	SD	Mean	SD
Males						
Educ. 1	0.2458500	0.084387	0.1183303	0.0384901	0.105604*	0.0294281
Educ. 2	0.4618761	0.1376215	0.1169693	0.044695	0.4019692	0.1120151
Educ. 3	0.7912367	0.2168615	0.1168054	0.0580768	0.7093672	0.1976764
Females						
Educ. 1	0.3968448	0.1477369	0.1214004	0.0305010	0.3990844	0.1122483
Educ. 2	0.4075402	0.116207	0.1112188	0.0363324	0.3096856	0.0871036
Educ. 3	0.5005796	0.1533306	0.1302665	0.0581591	0.2861009	0.0804700

* This variable is not significant

Table 7 Wage and non-labour income elasticities

	Total elasticity		Elasticity on the probability of being a potential participant		Elasticity on the expected number of counts conditioned on $A_i = 0$	
	Mean	SD	Mean	SD	Mean	SD
Males						
Wage	0.301224	0.209104	0.301224	0.209104		
Nlabinc	0.2172463	0.2064855	0.124532	0.1539088	0.0927143	0.0871089
Females						
Wage	0.3422371	0.1441252	0.2226433	0.1441252	0.1195938	0
Nlabinc	0.3130124	0.218825	0.1888824	0.1686333	0.1241299	0.086616

Starting with total marginal effects, the values are increasing with educational level. However, the analysis of the partial marginal effects of these variables on the probability of participating and on the expected frequency conditioned on participating provides a more detailed picture of their influence. For males, the probability of belonging to the Not-Always-Zero group increases in 11 % points compared to the previous category, regardless the initial educational level. In the case of females, these marginal effects are slightly larger—between 11 and 13 % points.

Regarding the effect of education on the frequency of participation, there is more variability in the values of marginal effects depending on the starting level of education. Male expected number of counts increases sharply with education. On the contrary, although education has also a positive influence on female frequency of attendance, the positive effect slightly decreases with the educational level. Nevertheless, the average increase in frequency is less than one time in 4 weeks in all cases.

Regarding the influence of the economic variables, all computed elasticities are below one. Nevertheless, the probability of being a potential participant is more sensitive to changes in wages or non-labour income that the expected frequency of attendance. Moreover, hourly earnings have a greater effect on individual decisions about cultural activities than non-labour income.

The elasticities shown in Table 7 also indicate that females are more sensitive to changes in earnings and non-labour income than males when studying the decision to participate in cultural activities and the frequency of participation. This result is consistent with other studies on time allocation. Specifically, the research on labour economics often finds that labour supply elasticities are higher for females. It seems that male allocation of time is not so conditioned by wages or non-labour income.[12]

5 Conclusions

This paper analyses individuals' decisions on the frequency of participation in cultural activities. In particular, we focus on passive cultural activities: visiting museums and monuments, attending theatre, ballet, classical dance, concerts and cinema.

Given that cultural activities are characterised by a high proportion of individuals who do not participate in them during the time period covered by the survey, 4 weeks, in the first part of our paper, we compare two methodologies that consider two reasons for explaining non-participation: some individuals may have no interest at all in these activities, whereas other people are potential participants but they have not demanded them during the period. The two models specified and estimated are the zero-inflated negative binomial count data model and the double-hurdle model with independent errors. The ZINB specification assumes that the dependent variable only takes integer and non-negative values, whereas the double-hurdle specification assumes that the dependent variable is continuous.

The database used is the Spanish Time Use Survey 2002–2003 and the sample consists of people between 18 and 65 years old. We run separate estimates by gender, and the set of covariates includes personal and family characteristics, labour status, earnings, non-labour income, and dummies for the quarter of the year and place of residence. Our first conclusion is that the ZINB model is preferred to the double-hurdle specification.

In the second part of our paper, we provide additional evidence on the effect of education and economic covariates on cultural involvement by computing the marginal effect of these variables on cultural participation and frequency. These factors are generally considered as important determinants of individual participation in cultural activities. Our results reveal that they tend to have a high degree of significance and have a positive influence on both the probability of being a potential participant and the frequency of participation. Specifically, an increase in education rises the probability of being a potential participant in about 11 percentage points, regardless of the starting level of education. Moreover, the

[12] See, for example, Bargain et al. (2014).

elasticities reveal that earnings and non-labour income have a greater influence on the probability of being a potential participant than on the frequency of participation. However, all elasticities are below one; however, wage elasticities are greater than non-labour income elasticities.

Summing up, both education and income-related variables are important determinants of cultural event attendance and have a separate and positive effect on individual cultural demand, besides the indirect influence of education through its effect on wages.

Regarding gender, the main differences between males and females are the effect of wage and labour status. Neither of these variables affects male frequency decisions. However, female frequency of attendance increases with wage and decreases when they are working. Moreover, female cultural participation is more sensitive to earnings and non-labour income than male participation.

Our results suggest that cultural promotion policies should be focused on the most disadvantaged population in terms of education and earnings. Also, policies reconciling work and family life will likely encourage female and male attendance at cultural events because our estimates show that labour status and family variables are deterrents of participation. In recent years, there has been a debate in Spain on the difficulty of reconciling work and family life due to the prevailing working times; many workers have split shifts and a long lunch break. A change in job schedules could foster social participation in cultural activities, in addition to its effect on work–life balance.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Tables 8 and 9.

Table 8 Descriptive statistics (females)

	Definition	Mean	SD	Min	Max
Age	Age of respondent	41.60389	13.30683	18	65
Married	1 if respondent is married, 0 otherwise	0.646946	0.477936	0	1
No. child ≤12	Number of children aged 12 years or younger	0.379120	0.715960	0	6
Quart. 1	1 if month is January, February or March, 0 otherwise	0.269806	0.443874	0	1
Quart. 2	1 if month is April, May or June, 0 otherwise	0.261276	0.439345	0	1
Quart. 3	1 if month is July, August or September, 0 otherwise	0.225998	0.418252	0	1
Urb. 2[a]	1 if respondent lives in a township with more than 100,000 inhabitants (and no provincial capital), 0 otherwise	0.083316	0.276369	0	1
Urb. 3[a]	1 if respondent lives in a township with fewer than 100,000 inhabitants (and no provincial capital), 0 otherwise	0.533675	0.498882	0	1
Adult3	1 if respondent lives in a household with more than 2 adults, 0 otherwise	0.444285	0.496903	0	1
Educ. 1[b]	1 if respondent has primary education, 0 otherwise	0.340703	0.473962	0	1
Educ. 2[b]	1 if respondent has high school education or vocational training, 0 otherwise	0.25377	0.435182	0	1
Educ. 3[b]	1 if respondent has college education, 0 otherwise	0.146094	0.353212	0	1
Worker	1 if respondent has a job, 0 otherwise	0.388673	0.487465	0	1
Log(wage)	Logarithm of observed hourly earnings for workers	1.208328	0.540560	−0.48016	5.75987
	Logarithm of hourly predicted earnings for non-workers: l wage is computed from a wage equation through Heckman's two-stage method				
Nlabinc	Non-labour individual income, calculated as income from other household members	1421.474	991.8829	0	6000

[a] The reference category is the provincial capitals

[b] The reference category is uneducated individual

Table 9 Descriptive statistics (males)

Variable		Mean	SD	Min.	Max.
Age	Age of respondent	41.19757	13.39117	18	65
Married	1 if respondent is married, 0 otherwise	0.626937	0.483638	0	1
No. child. ≤12	Number of children aged 12 years or younger	0.364381	0.710801	0	6
Quart. 1	1 if month is January, February or March; 0 otherwise	0.280325	0.449176	0	1
Quart. 2	1 if month is April, May or June, 0 otherwise	0.258986	0.438096	0	1
Quart. 3	1 if month is July, August or September, 0 otherwise	0.226613	0.418657	0	1
Urb. 2[a]	1 if respondent lives in a township with more than 100000 inhabitants (and no provincial capital), 0 otherwise	0.080893	0.272681	0	1
Urb. 3[a]	1 if respondent lives in a township with fewer than 100000 inhabitants (and no provincial capital), 0 otherwise	0.546045	0.497896	0	1
Adult3	1 if respondent lives in a household with more than 2 adults, 0 otherwise	0.472211	0.499247	0	1
Educ. 1[b]	1 if respondent has primary education, 0 otherwise	0.345882	0.475674	0	1
Educ. 2[b]	1 if respondent has high school education or vocational training, 0 otherwise	0.284787	0.451331	0	1
Educ. 3[b]	1 if respondent has college education, 0 otherwise	0.144665	0.351777	0	1
Worker	1 if respondent has a job, 0 otherwise	0.705071	0.456029	0	1
Log(wage)	Logarithm of observed hourly earnings for workers	1.644886	0.508677	−0.61771	4.86605
	Logarithm of hourly predicted earnings for non-workers				
Nlabinc	Non-labour individual income, calculated as income from other household members	1065.343	1000.933	0	6000

[a] The reference category is the provincial capitals

[b] The reference category is uneducated individual

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