Analysing the popular music audience: determinants of participation and frequency of attendance

Juan D. Montoro-Pons Manuel Cuadrado García and Trinidad Casasús-Estellés[1]

Abstract

The past decade has witnessed a gradual shift in the popular music audience leading to the predominance of live performances as the main revenue source in the industry. Whether this trend is sustainable and how it relates to other sectors, mainly the recorded music industry, crucially depends on consumer's demand. We analyse the demand for live popular music by resorting to data by the 2010-11 Survey for Cultural Habits and Practices in Spain. The aim of this paper is twofold. Firstly, to determine the factors that explain frequency of attendance to live performances and how it relates to media participation. Secondly, to classify consumers by identifying different demand segments.

Keywords: Live music attendance, cultural capital, media-based consumption, zero-inflated count model

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[1] *Juan D. Montoro-Pons* is PhD in Economics and Associate Professor of Quantitative Economics at the University of Valencia. His research interests lie in Public Choice and Institutional Economics, and Cultural Economics. In this latter field he has undertaken quantitative research on the cultural industries with a special focus on the popular music industry. Works in this area include the analysis of the demand, both in live and prerecorded markets, the impact of the legal system on the enforcement of intellectual property rights, and the analysis of commercial success by means of charts analysis. *Manuel Cuadrado-García* is PhD in economics and associate professor of marketing at the University of Valencia, Spain. His main area of research is marketing culture and the arts. He has carried out and published several theoretical and empirical studies from both consumer and management perspectives in sectors such as cinema, theatre, music and museums. *Trinidad Casasús-Estellés*, PhD in Mathematics by the University of Valencia and MA in Economics by the European University Institute of Florence, is Associate Professor at the Mathematics for Economics and Business Department and Member of the International Economics Institute of the University of Valencia. She would like to thank the partial support of the project TIN2008-06872-C04-02 of the Ministerio de Ciencia y Tecnología, Spain.

1 Introduction

The past decade has witnessed a shift in the popular music market worldwide, with the live industry outperforming the more traditional recorded music sector. Spain is a clear case study: recorded music revenues have declined by a mean annual rate of -13% — from 633 million in 2001 euros to 179 in 2010 — over the period 2001-2010. In contrast, live performance revenues have grown at an annual rate of 8.4% — from 85 to 173.5 million euros over the same period. Indeed, in 2011 live music turnout has overtaken that of prerecorded music in Spain.

However remarkable at the aggregate, individual level figures provide us with a deeper insight on the process. Comparing data by the 2006 and 2010 waves of the *Survey for Habits and Cultural Practices in Spain* — from now on SHCP2006 and SHCP2010 —[2] we find noteworthy similarities and differences in the popular music audience over time.

Attendance to live popular music performances, measured in relative terms,[3] has hardly changed over time: roughly 12% of those sampled attended — i.e. 88% had not — to a live performance over the past three months. The distribution of attendance in both years is, as would be expected, highly skewed with a long tail to the right. This is an interesting finding in itself, as it implies that revenue growth in the industry — from 155m euros in 2006 to 182m in 2010 — has been primarily driven by price increases.[4] Moreover, attendance in Spain has a strong seasonal pattern, with a peak around the second term of the year — 40% of the observed frequency — and a trough in the fourth term — 14% to 15% of the observed frequency depending on the year.

Overall, this reflects an increasing relative economic relevance of live music which has become the main market in the popular music in-

2 The SHCP is a survey based research which offers individual level information about cultural participation by the Spanish population over 15. It is undertaken by the Spanish Ministry of Culture.

3 Certainly, absolute data on attendance can increase if population grows. However data for population over 15, the segment targeted by the SHCP, has only slightly increased from 30,61m in 2007 to 31,31m in 2011.

4 A fact that is reinforced using SGAE (2011) aggregate data on attendance, with a reported audience of 28 million in 2006 and 31 million in 2010. This agrees with Krueger (2005) findings on price dynamics of live performances in the US.

dustry. On the grounds of this increasing relevance, a deeper analysis of the live popular music industry applies.

This paper aims at empirically explaining consumer behavior in the live popular music sector. By using a representative survey on cultural participation for the Spanish population over 15 we shed light on the factors that determine the frequency of participation in live music performances by the Spanish audience. Three determinants stand out:

- Sociodemographic variables. We find statistically significant gender-effects — female are less likely to participate and/or do it less frequently — and time-effects — with individuals' time-restrictions being a strong determinant of of participation and/or its frequency.

- Educational attainment and cultural capital, i.e. past consumption and the building up of knowledge which proxy using variables such as music listening or reading habits to mention two. Both are traits that also explain other forms of cultural consumption.

- Media participation. Somehow related to the cultural capital, media participation can be seen as a complement to popular music attendance. However one should note that consumers engagement with recorded music has been significantly altered by the digitization of music and its widespread availability over the Internet. In this sense the results point to significant differences between the effect of purchases — that increase the likelihood of attendance and its frequency — and copying of recorded music[5] — only increases the frequency of participation.

Furthermore, heterogeneity of cultural consumption arises as a natural extension of our estimation strategy. Given that most individuals in

5 By copying we mean any alternative use of recorded music, which includes copying from peers but also downloading from the Internet or file-sharing from peer-2-peer networks.

the population are non-attendants, one could ask whether this is a uniform group. As the results show, non-attendants can be classified in terms of their likelihood of never-attending by resorting to a zero-inflated count model which allows us to single out different behavioral patterns in the consumption and use of popular music.

The paper is organized as follows. Firstly, we start with a review of the literature and the general setup for cultural participation applied to live music consumption. Secondly we introduce the empirical work. Here we start by describing and summarizing the dataset, and continue by showing the main findings that stem from the application of the proposed testing strategy. Finally, we close with the discussion of the main results and some conclusions.

2 The consumption of live popular music

2.1 Literature review

Attendance to live popular music can be analyzed from the economic perspective of cultural participation. From a microeconomic standpoint, current engagement with the arts is primarily determined by previous consumption experiences in which individuals build up a stock of *cultural capital*. This can be either seen as the outcome of a habits formation process or rational addiction,[6] or as the discovery of tastes derived by a learning by consuming approach.[7]

While the theoretical model can be seen as the solution of an individuals's maximization process, the testing of its implications entails dealing with the fuzziness of the concept of cultural capital and, more important, trying to capture it with current available information. Here it is worth noting that the microeconometric estimation of demand mo-

6 See the Stigler & Becker (1977) household production model and its application to culture and the arts by Ateca-Amestoy (2007).

7 As in the Levy-Garboua & Montmarquette (1996) model of theater demand.

dels for the cultural consumer are primarily based on survey data.[8] What are the main findings in the empirical literature of cultural participation?

From the broader perspective of the performing arts, Seaman (2006) offers a detailed review of the applied literature on participation. Overall, the econometric findings point to education standing out as the most strong determinant of demand, even more than income — specially in survey-based studies —; the relevance of quality, even though trying to capture it is not straightforward; and the need to include the dynamics that emerges in cultural consumption, be it the outcome of rational addiction, inertia or a learning-by-consuming process. Other findings relate to the price inelasticity of performing arts, the limited evidence with regards to complements and substitutes and the fact that some non-standard lifestyle and socialization variables may play a role.

As for the empirical evidence in popular music consumption, it is interesting to note that very few papers deal with it from a microeconometric perspective, and even less analyze the demand for live popular music performances. Next, we review five papers that deal with popular music consumption. All of them share a similar approach by applying an econometric strategy — usually some qualitative dependent variable estimation framework — to nationwide individual-level survey data.

The main research question in van Eijck (2001) is the analysis and determinants of musical tastes — as the variety of music genres of choice — in the Netherlands. By clustering individuals using a factor model, the author finds that popular music consumption is negatively related to age, education and active music participation. On the other and, gender and occupational status do not have a significant effect.

Prieto-Rodríguez & Fernández-Blanco (2000) analyze listening music habits in Spain, trying to identify what are the traits, if any, that popular music and classical music listeners share. Using a bivariate probit model, the econometric findings point to a negative age effect and a nonlinear effect of education on popular music listening and a positive one on classical music listening. Time availability also plays a key role in explai-

8 These pose specific practical and econometric problems, mainly derived from the unobserved heterogeneity between individuals and how it is tackled within the research framework.

ning participation in both activities, while there is no evidence of gender effects.

The analysis of Canadian audiences for years 1992 and 1998 is undertaken by Fisher & Preece (2003). Based on reported attendance, they segment the audience in classical music attenders, i.e. *snobs*, and classical and other music attenders, *omnivores*. Their findings suggest that education, gender — i.e., being female —, income, age and other forms of cultural participation (reading and going to the movies) are strongly associated with the incidence of snobs. As for omnivores, the main difference is that they are younger; other variables have similar qualitative effects on both groups.

Favaro & Frateschi (2007) analyze attendance to classical and popular music performances in Italy. They use a multinomial logit model to estimate observed consumer choices — only classical/only popular/both. Their findings point to age and gender – being female — being positively related to attending both types of events and negatively related to only popular music attendance. Education and time availability have a positive effect on attendance in all groups, while results for occupational status are ambiguous.

Montoro-Pons & Cuadrado-García (2011) analyze live and prerecorded popular music participation in Spain. The authors estimate a bivariate probit model for attendance and purchase of music in two different time frameworks. The findings show some similarities in the pattern of participation in both markets — there is a strong gender-effect, i.e. being female, has a negative effect on attendance and purchases, and cultural capital has a positive effect — but also some differences — time availability, the use of technology and economic-related variables have asymmetric effect on participation. More interesting, by using a recursive specification the authors find a direct effect of recorded music consumption on live attendance but not the reverse, which they relate to recent changes in consumption of prerecorded music.

Finally, from an unrelated methodological standpoint, Earl (2001) analyzes attenders' motivations to live popular music events. By using subjective personal introspection, the author concludes that attendance

to live music events has to be driven by factors different to those of the demand of music itself, one of them being what he labels the *pilgrimage motivation*, i.e. the social ritual surrounding the participation in such live events.

The previous review raises two questions. First, of the few papers that analyze popular music consumption, only one includes in the analysis live and prerecorded consumption. If we acknowledge that there is a link between media consumption and live attendance, then one should include both aspects in the analysis. Second, all of the papers deal with participation — as the binary choice made by consumers — but none with its frequency — how many times?. In this paper we fill this gap in the literature by bringing these features together. We jointly model participation and frequency of participation using a unified framework, i.e. a zero-inflated count specification. In other words, our estimates allow us to identify what factors determine participation and what factors affect the number of times an individual attends. Additionally, we include media consumption as control variables that ultimately allow us to identify the correlation between live and recorded music decisions. Next, we specify an empirical model for the frequency of live popular music attendance and define a testing strategy.

2.2 Explaining attendance

We assume that individual i frequency of participation —number of concerts— per unit of time can be expressed as:

$$y_i = f(x_i) = f(Soc_i, Ec_i, Ed_i, Geog_i, Cult_i, Med_i, Eq_i, Pref_i) \quad (1)$$

with Soc_i being individual i socio-demographic characteristics, Ec_i economic factors, Ed_i educational attainment, $Geog_i$ geographical variables, $Cult_i$ cultural capital variables, Med_i media-consumption related variables, Eq_i cultural equipment and other physical capital in the household and $Pref_i$ revealed preferences on live music. We acknowledge that media-based consumption is a way of accumulating cultural capital. However we explicitly model it as a separate variable to single it out as the main means by which consumers accumulate cultural capital.

Expression (1) allows us to estimate the average profile of the attender. This implies interpreting the individual impact of each covariate on the response^{y}, and test some well established regularities previously found in the literature, mainly the impact of income, time restrictions, and, more specifically, the relevance of education and cultural capital in explaining consumption.

Further, it accounts for the net impact of media-based consumption in its double role as a substitute of live participation —i.e. as a means of satisfying music-related needs—, and as an addictive mechanism in that it leads to the gathering and accumulation of knowledge, and hence of consumption capital, about music. Additionally we are also interested in disentangling the different effect on attendance, if any, of recorded music consumption, i.e the purchase of music recording, and other forms of music use, such as copying, sharing and downloading from the Internet.

Finally, and based on the analysis of frequency of participation, the model allows the identification of the different segments that make up the market. This will allow us to characterize different behavioral patterns according to segment membership which, ultimately, could be a helpful tool for practical purposes.

2.3 Model specification

The response variable y in expression (1) is the outcome of a count process. The most simple setup for this model is to assume for y a Poisson process, in which the mean of the endogenous variable — $\mu = E[y]$ — is a function of a set of covariates x_i, such that

$$\mu_i = \exp(x'_i, \beta) \qquad (2)$$

The main drawback of the Poisson distribution is that it assumes equidispersion, i.e. equal mean and variance, which can be a rather strong assumption.When overdispersion is an issue,[9] one can resort to alternative specifications such as the negative binomial model that allows for a more flexible modeling of the variance of the conditional

9 Indeed, after examination of the descriptive statistics for frequency of attendance in table, this seems to be the case with our dataset.

response. In this case y ~ Poisson(y|μ*v*), being μ the mean of a poisson count process and *v* a random process that introduces multiplicative randomness.[10]

Assuming E(*v*) = 1 and Var(*v*) = σ^2, then the mean is E(y) = μ, but dispersion increases compared to a Poisson distribution. If we model the mean of this process in terms of the regressors in expression (2), we set

$$\mu = \exp(x'\beta) \tag{3}$$

Then one can estimate the set of parameters β by maximum likelihood using numerical methods.

Note that the negative binomial distribution is usually preferred to the Poisson model as it accommodates overdispersion. However, as Cameron & Trivedi (2005) note, the negative binomial model is less robust to distributional misspecification than the Poisson.

A second and somewhat related issue when modeling count data is that of excess zeros, i.e a higher than expected frequency of zeroes in the dataset. In our case the excess of zeros implies that the frequency of non-attendance is greater than what would be predicted by a count model. To model a count process with inflation of zeros, one can resort to a zero-inflated model in which a binary process and a count process are combined. Let f(·) represent the binary process and g(·) the count. Then the response probability, suppressing the regressors for simplicity, is given by:

$$P(y_i|x_i) = f(0) + (1 - f(0))\, g(y_i) \tag{4}$$

In this setup a zero can be either the outcome of the inflation part, when f(0) = 1 or a count, for f(0) = 0. Interestingly, there are different underlying behavioral assumptions in both kind of zeros. That allows us to interpret the results in terms of individual preferences.

10 In fact, the negative binomial distribution models the multiplicative randomness as a gamma distribution.

3 Empirical work

3.1 The Data

To estimate expression (1) we use secondary data provided by the SHCP2010. The SHCP2010 is a research that aims to describe cultural practices and habits of the Spanish population over 15. Its main objective is to provide information about population demand for the activities within the different cultural sectors.

The survey is carried out by the Spanish Ministry of Culture — as part of the National Statistics Planning — and complies with the guidelines by the EUROSTAT's working group on Cultural Statistics. The National Statistics Agency (INE) collaborates in the methodological underpinnings of the sampling design, which is a two stage sampling method with stratified primary sampling units. The theoretical sample size was set to 16,400 second stage units , i.e. individuals. The survey was conducted using personal interviews between March 2010 and February 2011.

As for its scope, the survey covers individuals' involvement with heritage, reading, performing arts, classical and popular music concerts, cinema and video, prerecorded music, television and radio, computer and the Internet, and other practices related to culture and/or leisure.

With regards to live popular music attendance the survey reports frequency of attendance as the answer to how many times the survey-taker attended to a popular music live concert in the last three months. This will be the dependent variable in expression (1). Table 1 tabulates the response variable. From it we see that non-attendance is the most frequent outcome — 88% of the sample — a result that points to a zero-inflated process. Moreover only 4.8% of those surveyed attended at least twice to a performance in the past three months.

Not surprisingly, live attendance and media based consumption and use are correlated. Accumulation of cultural capital can take different forms but recorded music is still a way of building up knowledge about acts and music. Using a binary variable for attendance, we compute the tetrachoric correlation between alternative forms of popular music use

— copying and/or downloading — and consumption — physical or digital purchases. Table 2 shows the results. Interestingly this correlation is strongest between copying and attendance and weakest between recorded music purchasing and copying. Obviously these are just raw correlations and we must take into account covariates that could partially explain them. Next we enumerate them.

First, socio-demographic characteristics. In this group we include gender (Female), age — and its square to account for nonlinearities —, marital status (Single) and whether the survey-taker is responsible for children under the age of 18 living in their same household (Child). We also account for the size of the household giving a breakdown on age brackets: number of individuals in the household over 18 (N-over18), between 15 and 18 (N-over15), between 10 and 18 (N-over10) and less than 10 (N-less10).

Second, economic variables. One drawback of the SHCP2010 is that it does not include information about the survey-taker income. Therefore we need use indirect income indicators, such as labor market situation (variables Student, Employer, Employee, Unemployed, Retired, and Househusband) and education attainment variables (variables High-School, Vocational, and University). Overall it is reasonable to assume these will be correlated with income, although educational variables also will give a rough approximation to the cultural capital individuals hold. Nevertheless there are other variables that we expect to be correlated with income. Whenever this is the case, we point it out.

Third, geographical variables. We include a dummy for each of the 17 regions in Spain. We include them to control for regional income differences, supply side factors and other latent regional differences. However these are not included in the regression output as they do not have a direct interpretation and that would unnecessarily complicate the presentation of the results. Additionally, we also include a variable City-Size. This provides the following classification for cities:

- Province capital (CitySize1);
- Population over 100,000 (CitySize2);

- Population between 50,000 and 100,000 (CitySize3)
- Population between 10,000 and 50,000 (CitySize4).

The reference case is that of cities with less than 10,000 inhabitants that are not province capitals.

Fourth, we need to take into account music cultural capital. Here we include, as it has been mentioned, the use of media for the satisfaction of music needs. Three dummies are considered. The variable Media takes on value 0/1 depending on whether the survey taker purchased recorded music and/or downloaded or copied recorded music over the past three months. In order to be able to discriminate between both effects on attendance — but at the cost of an increasing model complexity as it will be shown — we also split Media in two: Purchase and Copy.

Additionally, we include other variables that account for the accumulation of consumption capital specific to music. Within this category we include:

- A variable to control for daily music listening time in minutes (Minutes);
- a dummy accounting for watching music programs on TV (TVMusic);
- a dummy for reading cultural magazines at least once a month (Magazines) and a dummy for those that read music-related reviews (Critics)
- finally, two dummies accounting for the active involvement in music by means of playing an instrument, singing or performing any other activity related to music (Active), and the participation in courses related to music (Courses).

Fifth, we also include variables that measure a household physical capital. The survey includes information for music related equipment (music instruments, radio sets, CD players, portable disc players, MP3 players, tape players, turntables and the like) and other cultural

equipment in the household (TV sets, cameras and videocams, videogame consoles, ebook reader, number of books, computers, smartphone, broadband and mobile broadband mainly). This is relevant as physical equipment is either basic for listening to music or related to it and, therefore, to habit formation. However it should be noted that we expect physical equipment to be correlated to household income due to the lack of a measure for it. This, in turn, makes the estimated effect for these variables rather imprecise and very likely to be correlated with other control variables. Moreover, the large number of variables in this group calls for a dimension reduction for estimation purposes. To do so, we summarize all the information about music equipment and physical capital, by using a principal components analysis. This reduces the number of variables from 19 to 6 (3 for music related equipment and 3 for other physical capital) which still capture over 50% of the total variance. As in the case of regional dummies, we will not include these components in our estimation tables as they will be uninformative and will interfere with the interpretation of the main results.

Sixth, Internet variables. We already have considered a broadband Internet connection as part of the physical capital of the household. However we also include as separate variables being a user of file sharing networks (P2P) and of direct downloads services (DirectDownload) in order to capture for potential substitution and exposition effects in the consumption of popular music.

Finally, we also include the self reported valuation of the survey taker (Valuation) in popular music live performances. It is measured as the interest of the individual in popular music performances in a 0-10 scale. Here we aim at proxying underlying preferences for this kind of cultural events. Table 3 lists all the above variables and their main statistics.

3.2 Estimation results

3.2.1 A basic count model

We start by estimating the frequency of attendance by using a negative binomial specification as a benchmark model.[11] The main results are shown in table 4. All tables include estimates — except for the dummies for 17 Spanish regions and the physical capital and music-related equipment components that are omitted from the output for the sake of simplicity — robust standard errors (below in parenthesis), significance level (*0.1,**0.05), and, at the bottom of the table, the log likelihood, and an overall significance test and its p-value. Note that all estimation results take into account survey design weights.

Some results are worth noting. Firstly, and after controlling for other covariates, the observed seasonal pattern in the response variable is statistically significant for the second and fourth term. Taking as reference the first term of the year, frequency of attendance is significantly higher in the second term and lower in the fourth term with no statistically significant effect in the third term of the year.

Secondly, socio-demographic characteristics are relevant to understand the profile of live popular music consumers. Female are less likely to attend than male, while age affects negatively attendance and although only the nonlinear part of age is significant for models 1 and 2, a joint significance test rejects the null in all three cases. Consistently with similar works in other cultural fields, single individuals are more likely to participate than those in a relation, although after controlling for other covariates, having children to take care of was not significant. However, number of household members below 10 years old had a clear negative impact, which could partially explain the lack of significance of the variable Children. No labor market related variable was significant except for Retired; this could account for the fact that cultural participation is time intensive and retirees have plenty of it.

11 The negative binomial model allows us to accommodate for overdispersion, which is the case in the dataset. Being the mean attendance 0.6, and variance 1.39 equidispersion can be rejected.

Thirdly, cultural capital variables are relevant. Educational attainment — vocational and higher education positively affect attendance —, and variables related to active creation, or the gathering of information and knowledge by individuals — participation in courses, reading of cultural magazines or of critics evaluations, and daily average number of minutes listening to music — all have the expected sign.

Fourthly, as for Internet variables, we see that being a file-sharing user has no significant effect while being a downloader has a positive effect. This result is consistent with a positive sampling or exposition effect of recorded music on attendance. An effect that also stands out if we include the variable *Media* , individuals that purchased or copied music, which is positive and significant — Model 2 in the table. In this case we drop the covariates P2P and DirectDownload as there would be a perfect pairwise correlation among these and Media. Finally in Model 3 we split the net effect of media into media consumption through purchase and through download-sharing-copying. Interestingly, we note that the effect of buying on participation is greater in magnitude than that of copying. This could be due to the fact that those who purchase recorded music show, in general, a greater willingness to pay for music (hence also for live music).

3.2.2 Estimation of a zero-inflated count model

The high frequency of non-participation, see table 1, is very likely due to an excess of zeros in the dataset which, on the other hand, could be the cause of overdispersion. To address this we resort to the estimation of a zero-inflated count model, as per expression (4). By so doing we are assuming that the population is composed of two subpopulations: one the frequency of attendance of which always takes on value 0, i.e. non-attenders, and one driven by a count process.

Table 5 shows the estimation results. For each model the table shows estimation results for the negative binomial model — the count part — and for the likelihood of the response being always zero — the inflation part.

Starting with Model 1 and going through the inflation part, we see that non-attendance is explained by very few variables. First, the seasonal pattern is reinforced, with non-participation being negatively related to those taking the survey in the second term. Secondly, we see that socio-demographic variables matter: raising children increases the likelihood of non-attendance, while being single and student decreases its likelihood. Overall we consider that these findings point to a significant time-effect which is consistent with the nature of cultural participation. On the other hand self reported valuation on popular music decreases the likelihood of never attending. This result is linked to individual preferences that ultimately should drive attendance. Interestingly this determines whether an individual participates or not but does not alter the frequency of participation (as shown by the result in the count part of the model).

As for the count part of the model some results are consistent with estimates in table 4. Being female decreases the frequency of participation but interestingly it does not increases non-participation (as the inflation part estimates show), while being single increases it (again a time restriction effect). Surprisingly the frequency of participation increases with children but it is negatively affected by the number of children below 10 years old which may compensate for any positive effect. Overall the estimates signal to a strong time-effect.

None of the variables related to the labor market situation of the individual seem to affect the frequency of participation. However education (variables Vocational and University) does in a positive fashion, as expected. Overall we assume these account for a mixture of cultural capital and income effects.

Finally, cultural capital related variables — being actively involved in music creation and reading magazines or critics reviews — have the expected positive effect on attendance.

All of these results hold for Model 2. However one interesting result is related to the effect of media consumption on both parts of the model. While purchasing recorded music has a significant effect both on the inflation part –decreasing the likelihood of non-attendance — and the

count part — increasing the frequency — the effect of copying only affects the count part. Hence purchasing can be seen as an activity that signals to a very strong involvement with music, while copying points to a behavior that could be shared between both participants and non-participants.

4 Conclusions

This paper has undertaken an analysis of the frequency of attendance to the live music market. We have pursued two main goals. First to identify the profile of the consumer in the live performances popular music market, a market that is becoming increasingly relevant for artists and a new source of business for the industry as a whole. Second, to be able to segment the market and see, if any, the different behavioral patterns between the different demand groups.

Results provide the average profile of the live music consumer, a male, young, educated consumer with time availability and actively engaged in the media consumption of recorded music, both by purchasing and by copying and downloading music files and full albums.

However one must acknowledge that attendance data show a clear polarization between attenders and non-attenders, with 88% of the sample not having attended to a live performance in the three months prior to taking the survey. To better understand this behavior we have estimated a zero-inflated count model which allows us to segment the population based on observed features. In short, it classifies the population by discriminating between two types of zeros: those that, given their current situation,[12] have not attended over the period of reference but could have potentially attended, and those that will never attend.

The estimated model predicts that the likelihood of being an actual or potential attender is mainly driven by cultural capital related variables, a feature that is common to participation in other forms of art.

12 Think of individuals facing some type of restriction, i.e. time or income that yields a corner solution in their maximization problem. Even though they have preferences for live music, these would be latent.

Even though from the inflation part of the model we get a description of never-goers, we can exploit the predictions of the model and identify the size of the demand segment of potential attenders and condition it on other variables of the model. By using an ex-post Bayes rule, the model classifies 64% of the sampled individuals as zeroes, i.e. never-goers, while actual non-attendance in the sample is 88%. Hence a back of the envelope calculation leaves us with 22% of potential attenders or latent demand. This, on the other hand, increases potential participation from roughly 12% to 36% of the population.

Furthermore, the distribution of latent demand shows some interesting features: while 89.3% of female and 86.7% of male are non-attenders, the model estimates that roughly 64% of both groups are never-goers, leaving a slightly higher latent demand among women. From this same perspective, media participation offers an interesting insight: while actual non-participation is slightly larger among those that copy music —27% compared to 26% non-attendance in those that purchase— the estimated rate of never-goers is greater for those buying pre-recorded music, roughly 40%, than for those copying, equal to 34%. Maybe age interferes in this calculation as those that only copy and download music are also younger. In any case, this is an interesting result which is consistent with media participation fostering attendance.

To conclude, the above discussion shows that, as long as there is a latent demand, there is room to increase live popular music audiences. The key point is how to relax the restrictions that potential attenders face, something that goes beyond the scope of this paper. However it offers some hints that could be related to supply decisions, such as to smooth the obvious seasonal pattern of live music consumption or to remove some barriers to consumption (i.e. for those that are raising children) to mention two.

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6 Appendix

Attendance	Frequency	Percent	Cum.
0	12,752	88.03	88.03
1	1,039	7.17	95.2
2	315	2.17	97.38
3	159	1.1	98.47
4	58	0.4	98.87
5	54	0.37	99.25
6	30	0.21	99.45
7	12	0.08	99.54
8	7	0.05	99.59
9	6	0.04	99.63
10	26	0.18	99.81
11	1	0.01	99.81
12	11	0.08	99.89
15	6	0.04	99.93
20	7	0.05	99.98
24	1	0.01	99.99
30	1	0.01	99.99
50	1	0.01	100
Total	14,486	100	

Table 1: Frequency of attendance to live popular music performances over the past three months.

	Attendance	Purchase	Copy
Attendance	1.000		
Purchase	0.3312	1.000	
Copy	0.4288	0.2817	1.000

Table 2: Correlation matrix between live attendance and recorded music purchases and downloads

Variable	Mean	Std. Dev.
1. Music attendance and use		
Frequency of attendance	0.259	1.177
Purchase	0.114	0.318
Copy	0.193	0.395
2. Socio-demographic variables		
Female	0.520	0.500
Age	48.216	19.102
Single	0.361	0.480
Child	0.291	0.454
N-over18	2.553	1.083
N-over15	0.159	0.425
N-over10	0.132	0.390
3. Labor market related variables		
Employer	0.077	0.267
Employee	0.373	0.484
Unemployed	0.125	0.331
Student	0.094	0.292
Retired	0.199	0.399
Househusband	0.117	0.322
4. Educational attainment		
Vocational	0.135	0.342
HighSchool	0.136	0.343
University	0.17	0.376
5. Geographical related variables		
CitySize1	0.414	0.493
CitySize2	0.089	0.284
CitySize3	0.097	0.296
CitySize4	0.212	0.409
6. Proxies for cultural capital		
Minutes	32.019	39.2
TVMusic	0.098	0.298
Magazines	0.185	0.388
Critics	0.212	0.409
Active	0.102	0.303
Courses	0.009	0.097

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7. Music physical capital in the household		
Radio	0.919	0.273
Tape Player	0.525	0.499
Turntable	0.264	0.441
CD/DVD/Blue ray player	0.830	0.376
Digital music player	0.428	0.495
Walkman/Diskman	0.244	0.43
MP3 player	0.522	0.5
Mobile phone with music player	0.547	0.498
Number of music instruments owned	0.836	1.599
8. Other cultural physical capital in the household		
eBook reader	0.008	0.09
Number of books (physical format)	158.652	444.096
Number of encyclopedias (physical)	1.853	3.636
Number of books (digital format)	15.307	479.999
Number of encyclopedias (digital)	0.134	1.077
Number of computers	1.227	1.149
Broadband access	0.571	0.495
Mobile broadband	0.089	0.285
Smartphone	0.354	0.478
Videogame console	0.389	0.488
9. Involvement in copying and file-sharing in the Internet		
P2P	0.079	0.270
DirectDownload	0.109	0.312
10. Valuation of live popular music		
Valuation	6.044	3.17
Sample size	14,486	

Table 3: Summary statistics

	Model 1	Model 2	Model 3
Media		0.4332**	
		(0.0875)	
Purchase			0.4720**
			(0.1028)
Copy			0.2119**
			(0.0830)
Term 2	0.8158**	0.8143**	0.8148**
	(0.1027)	(0.1016)	(0.1018)
Term 3	-0.0105	-0.0100	-0.0110
	(0.1068)	(0.1062)	(0.1067)
Term 4	-0.3163**	-0.3145**	-0.3229**
	(0.1153)	(0.1166)	(0.1165)
Female	-0.3670**	-0.3390**	-0.3409**
	(0.0831)	(0.0826)	(0.0820)
Age	-0.0007	0.0026	-0.0027
	(0.0191)	(0.0191)	(0.0187)
Age^2	-0.0004*	-0.0004*	-0.0003
	(0.0002)	(0.0002)	(0.0002)
Single	0.3819**	0.3528**	0.3491**
	(0.0929)	(0.0924)	(0.0922)
Children	0.1994	0.2168	0.2164
	(0.1478)	(0.1478)	(0.1483)
Employer	0.2952	0.2784	0.3069
	(0.3299)	(0.3153)	(0.3012)
Employee	0.4571	0.4423	0.4746*
	(0.2925)	(0.2834)	(0.2683)
Unemployed	0.2319	0.2329	0.2685
	(0.3055)	(0.2974)	(0.2819)
Student	0.2753	0.2763	0.3224
	(0.3059)	(0.2985)	(0.2813)

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Retired	0.8379**	0.8228**	0.8295**
	(0.3853)	(0.3756)	(0.3639)
Househusband	0.4898	0.4995	0.5127
	(0.3493)	(0.3430)	(0.3305)
n-over18	-0.0967**	-0.0802**	-0.0813**
	(0.0396)	(0.0391)	(0.0390)
n-over15	0.0351	0.0385	0.0428
	(0.1033)	(0.1050)	(0.1051)
n-over10	-0.2139*	-0.2139*	-0.2226*
	(0.1177)	(0.1177)	(0.1171)
n-less10	-0.5133**	-0.5121**	-0.5152**
	(0.1021)	(0.1026)	(0.1019)
Vocational	0.3049**	0.3032**	0.2834**
	(0.1132)	(0.1129)	(0.1118)
HighSchool	0.1652	0.1471	0.1536
	(0.1418)	(0.1420)	(0.1414)
University	0.3036**	0.2755**	0.2690**
	(0.1077)	(0.1080)	(0.1088)
P2P	-0.0255		
	(0.1044)		
Download	0.1721**		
	(0.0862)		
Valuation	0.2016**	0.1956**	0.1983**
	(0.0233)	(0.0231)	(0.0230)
TVMusic	0.1243	0.0946	0.0949
	(0.1139)	(0.1112)	(0.1109)
Active	0.5240**	0.5040**	0.4922**
	(0.0985)	(0.0976)	(0.0985)
Courses	0.3340*	0.3683*	0.3264
	(0.2011)	(0.2181)	(0.2210)
Magazines	0.3193**	0.3116**	0.2930**
	(0.0854)	(0.0863)	(0.0878)

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Critics	0.4161**	0.4108**	0.3984**
	(0.0836)	(0.0837)	(0.0841)
Minutes	0.0033**	0.0030**	0.0029**
	(0.0008)	(0.0008)	(0.0008)
CitySize1	0.0861	0.0977	0.1029
	(0.1180)	(0.1177)	(0.1172)
CitySize2	-0.1714	-0.1688	-0.1710
	(0.1616)	(0.1616)	(0.1635)
CitySize3	-0.0858	-0.0819	-0.0640
	(0.1455)	(0.1454)	(0.1455)
CitySize4	-0.0756	-0.0717	-0.0699
	(0.1328)	(0.1309)	(0.1294)
ll	-1.78e+07 **	-1.77e+07 **	-1.77e+07 **
χ^2	1464.0106	1461.1826	1455.4334
p	0.0000	0.0000	0.0000

Table 4: Count model estimations for attendance to live popular music performances (negative binomial specification)

	Model 1		Model 2	
	Count	**Inflate**	**Count**	**Inflate**
Purchase			0.2227*	-0.5889**
			(0.1184)	(0.2394)
Copy			0.1948*	-0.2548
			(0.1182)	(0.2750)
Term 2	0.3055*	-1.1769**	0.2838*	-1.2829**
	(0.1598)	(0.3308)	(0.1658)	(0.3770)
Term 3	0.1262	0.2912	0.0721	0.1826
	(0.1671)	(0.2950)	(0.1633)	(0.2911)
Term 4	0.1703	1.0121**	0.1196	0.9412**
	(0.1817)	(0.2857)	(0.1753)	(0.2768)
Female	-0.2702**	0.1630	-0.2773**	0.0970
	(0.1016)	(0.1919)	(0.1027)	(0.1969)
Age	-0.0622**	-0.0574	-0.0593**	-0.0515
	(0.0280)	(0.0516)	(0.0282)	(0.0544)
Age^2	0.0005*	0.0009*	0.0005	0.0009
	(0.0003)	(0.0005)	(0.0003)	(0.0006)
Single	0.0571	-0.6101**	0.0513	-0.5992**
	(0.1566)	(0.2825)	(0.1596)	(0.3040)
Children	0.4455**	0.5604**	0.4414**	0.5255*
	(0.1776)	(0.2728)	(0.1771)	(0.2753)
Employer	-0.1101	-0.7790	-0.0417	-0.6503
	(0.6269)	(0.9783)	(0.6081)	(1.0374)
Employee	-0.2197	-1.2193	-0.1334	-1.0714
	(0.5730)	(0.9091)	(0.5423)	(0.9485)
Unemployed	-0.3163	-1.0081	-0.2463	-0.8999
	(0.5650)	(0.8943)	(0.5311)	(0.9270)
Student	-0.5788	-1.7952*	-0.4652	-1.6616
	(0.5836)	(0.9990)	(0.5439)	(1.0327)
Retired	0.6298	-0.4141	0.7235	-0.2340
	(0.6449)	(0.9456)	(0.6214)	(0.9883)
Househusband	-0.2710	-1.2970	-0.1487	-1.1017
	(0.6374)	(0.9978)	(0.6105)	(1.0257)
N-over18	-0.0477	0.1069	-0.0435	0.0895
	(0.0432)	(0.0912)	(0.0438)	(0.0936)
N-over15	0.0544	0.1842	0.0420	0.1590
	(0.1073)	(0.2196)	(0.1070)	(0.2190)
N-over10	-0.1217	0.1936	-0.1116	0.2088
	(0.1309)	(0.2277)	(0.1330)	(0.2359)
N-less10	-0.4054**	0.2040	-0.4211**	0.1864
	(0.1376)	(0.2235)	(0.1437)	(0.2380)

Vocational	0.3908**	0.2014	0.4071**	0.2808
	(0.1515)	(0.2702)	(0.1544)	(0.2766)
HighSchool	0.1050	0.0433	0.1248	0.1043
	(0.1417)	(0.2599)	(0.1439)	(0.2733)
University	0.2926**	-0.1262	0.3086**	-0.0325
	(0.1454)	(0.2672)	(0.1464)	(0.2723)
P2P	0.2525*	0.4927*		
	(0.1402)	(0.2890)		
Download	0.0734*	-0.5070*		
	(0.1064)	(0.2917)		
Valuation	0.0413	-0.3140**	0.0451	-0.3066**
	(0.0341)	(0.0412)	(0.0350)	(0.0417)
TVMusic	0.0277	-0.2136	0.0036	-0.2379
	(0.1208)	(0.2925)	(0.1252)	(0.3140)
Active	0.4895**	-0.1164	0.4894**	-0.0588
	(0.1202)	(0.2576)	(0.1212)	(0.2679)
Courses	0.2232	-0.8654	0.1569	-1.1011*
	(0.2474)	(0.5927)	(0.2534)	(0.6480)
Magazines	0.2184**	-0.1720	0.2146**	-0.0983
	(0.1107)	(0.2158)	(0.1094)	(0.2177)
Critics	0.3525**	-0.1879	0.3422**	-0.1777
	(0.1070)	(0.2012)	(0.1071)	(0.2052)
Minutes	0.0020	-0.0032	0.0018	-0.0032
	(0.0014)	(0.0036)	(0.0014)	(0.0037)
CitySize1	0.0455	-0.1474	0.0194	-0.1911
	(0.1571)	(0.2806)	(0.1596)	(0.2883)
CitySize2	-0.4095*	-0.5615	-0.4662**	-0.6704
	(0.2240)	(0.4529)	(0.2178)	(0.4429)
CitySize3	-0.2584	-0.5371	-0.2891	-0.6017
	(0.2183)	(0.4337)	(0.2351)	(0.4833)
CitySize4	0.0454	0.1112	0.0022	0.0464
	(0.1653)	(0.2819)	(0.1692)	(0.2924)
ll	-1.72e+07**		-1.72e+07**	
χ^2	389.8224		403.3236	
p-value	0.0000		0.0000	

Table 5: Zero inflated count model for frequency of attendance