Price Discrimination in the Concert Industry

Pascal Courty and Mario Pagliero[1]

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Abstract: Concert tickets can either be sold at a single price or at different prices to reflect the various levels of seating categories available. Here we consider how two product characteristics (the artist's age and venue capacity) influence the likelihood that pop music concert tickets will be sold at different prices. We argue that valuation heterogeneity, and thus the returns to using price discrimination, are higher for older artists and in larger venues. We test this hypothesis in a large dataset of concerts. By singling out variations in the two characteristics that are exogenous to the decision to price discriminate, we show that these characteristics have a large and significant impact on the use of price discrimination.

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[1] Pascal Courty, Department of Economics, European University Institute, Pascal.Courty@IUE.it; or Mario Pagliero, University of Turin, Department of Economics and Finance, and Collegio Carlo Alberto, Mario.Pagliero@unito.it. We would like to thank Stefania Di Gangi, Oege Dijk and Aikaterini Gousia and seminar participants at the University of Cyprus, Milano Bicocca, and ASSET08.

1-Introduction

Price discrimination is often introduced in economic textbooks as a way of stimulating the reader with vivid illustrations of the relevance of economic theory. Describing particular cases is one thing; but, ultimately, the theory should also be able to predict when firms will choose price discrimination rather than uniform pricing. This is a challenging task. One can easily think of instances of sellers who price discriminate in one market but then charge a uniform price in another market with similar features. Busse and Rysman (2005) and Clerides and Michis (2007) show that there is wide variation across markets and over time in the extent to which firms price discriminate. So how can economic theory help explain firms' decisions concerning the pricing strategy they choose?

We empirically study the determinants of second degree price discrimination in the popular music concert industry. This industry appealed to us for several reasons. To start with, Connolly and Krueger (2006) identify price discrimination as a key issue for future research, narrowing the question down to 'What determines the amount of price discrimination within concerts?' (2006, p. 63). We take up that question here as the focus of our study. Secondly, choosing the pop concert industry allows us to sidestep a problem typical of most applications in the literature, i.e., that price differences across products may be explained by variations in marginal cost rather than by price discrimination (Shepard (1991), Clerides (2004)). In our application, since variable costs are zero, this ambiguity does not occur. Finally, the concert industry offers a uniquely rich set of pricing policies set by independent firms under different market conditions.

We say that an artist price discriminates if seats at a given event are sold at different prices. In our sample, about 25 percent of the events offer uniform pricing (general admission) while the others use price discrimination (with at least two different prices corresponding to multiple seating categories). The main objective of this paper is to determine whether economic theory can help explain the decision to use price discrimination. The analysis proceeds in two steps.

First, we present a theoretical argument for why older artists and those performing in larger venues are more likely to price discriminate, *ceteris paribus*. Briefly stated, the intuition is that larger venues offer a greater variety of product quality (e.g., one of the main dimensions of quality, the distance to the stage, varies more within larger venues), and that older artists perform for an older and more diverse audience that is willing to pay more for quality.

We then provide evidence consistent with our main hypothesis. A key issue is whether we can single out exogenous variability in the age of the artist and venue capacity. We present theoretical arguments to support exogeneity in our empirical specification and also leverage the richness of our panel dataset to investigate robustness to many sources of potential endogeneity.

Surprisingly few studies have tried to test price discrimination theory (Stole, 2008). There are two notable exceptions. Verboven (1999) rejects a prediction on product line mark-ups and Nevo and Wolfram (2001) reject a simple comparative static prediction. These findings are not surprising, given that the industries considered were oligopolistic. In contrast, the concert industry much more closely resembles the textbook case of monopoly pricing, and we are the first to consider the basic choice between price discrimination and uniform pricing.

2-Theoretical background

Throughout this paper, we follow the literature and interpret the practice of selling vertically differentiated goods (seat quality) as screening under second degree price discrimination a la Mussa-Rosen. Strictly speaking, it could also be consistent with monopoly pricing in independent market segments, and the distinction is that, under the latter interpretation, there is no substitution across seating categories. This is debatable, and some economists would argue that both rationales correspond to price discrimination to the extent that, in both cases, the monopolist sells products with identical variable costs at different prices (Clerides, 2004). In any event, the distinction between these two rationales for price differentiation is not relevant for our work, because our main predictions hold independently. Keeping this nuance in mind, the contribution of this paper is to test whether sellers respond to price discrimination opportunities; we leave the question of whether differentiated pricing in our case study is an illustration of strict second degree price discrimination (in the sense that the sorting constraint binds) for future research.

A firm is expected to price discriminate when the cost of implementing price discrimination is lower than the increase in net revenue. In our case study, such costs may include the cost of adding a seating category, printing different tickets, segmenting the venue and enforcing property rights over seats (Miravete, 2007). The return to price discrimination depends on the cost function and on the distribution of consumer preferences (Anderson and Dana, 2008). One consideration specific to concert ticket pricing is that most costs are fixed and the physical space in each venue constrains the number of seats that can be offered in each category. This constraint is the key to our identification strategy.

Seller's decision to price discriminate

We borrow Rosen and Rosenfield's (1997) model of ticket pricing to express the seller's decision to price discriminate as a function of given characteristics such as venue capacity and consumer demand. A venue of capacity K can be split into n_s seats of quality s, s=l,h, where n_s is such that $n_l+n_h=K$. There are two types of consumers. Consumer θ=L,H values v^θ_s

a seat of quality s=l,h such that $v^\theta_h > v^\theta_l$, $v^H_s > v^L_s$, and $v^H_h - v^H_l > v^L_h - v^L_l$. As in the standard model of price discrimination, consumers value the high quality good more, the high type values any quality more than the low type, and the high type values an increment in quality more than the low type. For now, θ is left unspecified. In the empirical analysis, we will assume that θ=H represents an older (wealthier) and less price-sensitive public. There are not enough high types to fill the entire venue, but there are enough to fill the high quality seats. We do not consider the option of selling only high quality seats to the high types and leaving many seats unsold, because this is not realistic in the pop concert industry, where venues are often sold-out.

Under price discrimination, the monopolist fully extracts the surplus of the low type consumers, $p_l = v^L_l$, binds the incentive compatibility constraint of the high types, $p_h = v^L_l + (v^H_h - v^H_l)$, and earns revenue

$$\Pi^d = [n_l + n_h]v^L_l + n_h(v^H_h - v^H_l).$$

The first term in the RHS corresponds to the profits under uniform pricing, $\Pi^m = Kv^L_l$, since in order to sell-out, the monopolist cannot charge more than v^L_l. The gain from using price discrimination is $\Delta\Pi = \Pi^d - \Pi^m - C$, where C captures the fixed cost of implementing price discrimination, and can be expressed as

$$\Delta\Pi = n_h(v^H_h - v^H_l) - C \qquad (1).$$

The monopolist price discriminates when this expression is positive. It is now clear that the specific feature of our application, that the distribution of seat quality is exogenously given, greatly simplifies the expression of ΔΠ.[2]

[2] The main point is that production costs are absent in (1); only implementation costs influence the decision to price discriminate. In addition, (1) requires only comparing differences in willingness to pay for quality within individuals (not across individuals). To illustrate this point, consider the standard model of quality price discrimination where quantities are endogenous (Mussa and Rosen, 1978). Assume that there are n_θ consumers of type θ, and to make the analysis comparable to the one above, assume

Hypothesis

Assume that one observes concerts with different pricing policies. The theory predicts that price discrimination should take place when $\Delta\Pi>0$. For any given concert, however, the econometrician cannot observe both Π^d and Π^m and therefore cannot observe $\Delta\Pi$. But $\Delta\Pi$ is a function of demand and product characteristics, some of which are observed, and others of which are unobserved. Call the set of observed characteristics X. We can test the theory under two assumptions. First, for characteristic x in a subset $X_1 \subset X$, $\partial\Delta\Pi/\partial x$ is monotone in x. That is, we can sign the impact of the variables in X_1 on $\Delta\Pi$. Without loss of generality, we assume $\partial\Delta\Pi/\partial x>0$. The second assumption requires that, conditional upon X, the unobserved characteristics are not correlated with x. When these two assumptions hold, a test of the theory is

$$(\partial/\partial x)\Pr(PD=1|\, X)>0, \text{ for } x\in X_1 \tag{2}$$

where PD is a dummy variable equal to one if price discrimination is used ($\Delta\Pi>0$).[3] The impact of x on the probability of price discrimination can then be estimated using limited dependent variable models, and hypothesis (2) can be tested.

An observable variable in X may not qualify for testing the theory because (a) the theory does not allow signing $\partial\Delta\Pi/\partial x$ or (b) because it is correlated with unobserved variables that also influence $\Delta\Pi$, thus introducing an omitted variable problem. This latter point is subtle. Consider, for example, a measure of demand heterogeneity such as income inequality. Many

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again that selling only to high types is never optimal. Under uniform pricing, it is now optimal to sell high quality to all consumers. Price discrimination takes place when $\Delta\Pi=n_h(v^H{}_h-v^H{}_l)-C-(n_l+n_h)(v^L{}_h-v^L{}_l) >0$ which requires comparing within individual willingness to pay for quality across individuals.

[3] Conditional on X, PD is also a function of the unobserved characteristics. Under a structural approach, one would specify a joint density and integrate over these characteristics to obtain the probability of using price discrimination. Pr(PD=1) in (2) is a reduced form expression that omits this underlying structure.

specifications of consumer preferences imply that $\Delta\Pi$ increases with income inequality (condition a is satisfied). But income inequality is likely to be correlated with other unobserved variables that also influence $\Delta\Pi$, and condition (b) is violated. For example, income inequality may be correlated with income level (larger cities have higher average income and higher income inequality) and with other unobserved demand characteristics that influence $\Delta\Pi$ and that vary across cities, thereby preventing the researcher from identifying the predicted impact of income inequality on price discrimination, from a sample of concerts taking place in different cities.

In the rest of this paper, we argue that the above two conditions hold for two variables: the artist's age (A) and venue capacity (K). We will now propose an economic argument to sign $\partial\Delta\Pi/\partial x$, waiting to take up the issue of exogeneity until after having presented the case study and the variables in X.

The impact of venue size on the return to price discrimination

The prediction that increasing venue size increases the return to price discrimination holds so long as the quality differences across seats within a venue is positively correlated with venue size. For the sake of simplicity, we assume that the distance to the stage determines differentiation in seating quality. This assumption is without loss of generality if all the seats are identical and people only care about the distance to the stage. Even if there are additional dimensions of quality within a venue (e.g., standing room, regular seating, private balconies), heterogeneity in these dimensions is also likely to increase with venue size. In the context of the model, our assumption means that K is increased by adding seats farther away from the stage and therefore of lower quality. As K increases, the monopolist continues to sell to the n_h high types (which is fixed) while increasing sales to low types. The average quality of the seats in the low section decreases, and the high types' willingness to pay to upgrade to the high quality seats (v^H_h-v^H_l) increases. We conclude that ΔΠ increases with K.[4]

The impact of the age of the artist on the return to price discrimination

Two arguments suggest that age should increase the return to price discrimination, and both are based on the observation that the type of fans an artist has are determined largely by his/her age. First, there is ample anecdotal evidence that an artist's audience remains loyal over the artist's entire career. Fans make up a significant portion of the audience and form communities of devotees to particular musical styles or performers.[5] More systematic evidence points to the same conclusion. Empirical research in social psychology demonstrates that preferences for popular music are formed during a critical period of development associated with late adolescence and early adulthood and these preferences tend to prevail for the rest of one's life (Holbrook and Schindler (1989) and North and Hargreaves (1995)). This implies that young artists, singing to young crowds, acquire a fan base which then follows them throughout their career.[6] Over time, the artist's audience grows wealthier, and variability in earnings increases. In the language of the model, this can be described by an increase in the differential in willingness to pay amongst high types (v^H_h-v^H_l), which implies that the return to price discrimination increases with age.

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[4] A more general model would allow the monopolist to split a continuum of seats of different qualities into two categories, thereby endogenizing n_h. This could be done, for example, by assuming that there exists a continuum of types who self-select between low and high categories. The impact of adjusting n_h in response to an increase in K, however, has a second order effect on ΔΠ and therefore on the decision to price discriminate.

[5] The fandom phenomenon is related to the formation of social identities and has lasting consequences on preferences over music (Shuker, 2005).

[6] This is consistent with the observation that "demographics are partly responsible for the continued success of performers as diverse as the Rolling Stones, Bonnie Raitt, and Bob Dylan... This concert attendance is usually to 'revisit' the surviving performers---and their music---of the ageing fans' own generation." (Shuker 2005, p.194). This phenomenon is known in the industry as 'nostalgia rock' or 'adult-oriented rock' and it also holds for other musical styles such as country music (Sweetland, 2003).

Secondly, young artists generally do not appeal to older generations, while older artists can appeal to young and old alike. Young rappers, for example, attract mostly young fans, while older artists who are part of the classic rock generation are constantly being rediscovered by younger generations.[7,8] This implies that older artists are more likely to play for a more heterogeneous audience in terms of age and other dimensions. The return to price discrimination increases as the audience grows more diverse, because older and less price-sensitive individuals are more likely to buy high quality seats.[9] To conclude, both channels (ageing audience and more heterogeneous age composition of the audience) suggest that the return to price discrimination increases with the age of the artist.

The above discussion suggests that (holding everything else constant) price discrimination is more likely to take place (H1) in larger venues, $(\partial/\partial K)\Delta\Pi>0$, and (H2) for older artists, $(\partial/\partial A)\Delta\Pi>0$.[10]

3-Data

Our main dataset, which was collected by Billboard, covers over 21,000 concerts by the largest 100 sellers or artists in the industry over the 1992-2005 period. For each concert

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[7] This is consistent with the revival hypothesis stating that younger generations re-discover the music of older generations starting with recent ones and moving back in time (North and Hargreaves, 1995).

[8] Music professional report that “the younger audience might come in from listening to new bands like Razolight, then work their way backwards towards what we now think of as classic bands like The Police, or The Jam, and then further back to The Who and Led Zeppelin” (Music Week, 2007).

[9] Waddell et al. (2007, p.51) report that “older, less price-sensitive audiences (…) paying more for tickets appreciate having their own piece of ‘real-estate’ in a seat, but often they are adverse to a lawn or general admission situation. These fans like to know exactly where they will be and do not find sitting or standing in the grass appealing.”

[10] The impacts of K and A on Pr(PD=1) do not have a structural interpretation, since we have not specified how these variables enter the primitives of the model and have not specified the structure that generates variations in PD (variables unobserved by the econometrician that influence the decision to price discriminate; see footnote 3).

defined by a date, venue, and artist(s), we observe the different prices offered, and the capacity available.

In our sample, 56 percent of the concerts offer two price categories, 25 percent one, 15 percent three, and the other 4 percent offer four categories. To define our dependent variable, we say that a seller price discriminates (PD=1) if she does not offer all tickets at the same price. This definition cuts the sample between unsophisticated pricing (general admission) and sophisticated pricing (differentiated seating).

The two explanatory variables of interest are defined as follows. We measure A using the age of the performing artist when there is a single performer, or of the main performer when there are multiple artists in an act. For bands, we define A as the age of the band's main performer. In principle, one could consider alternative measures of age, such as the year the band was formed, or the year of the artist's first success.[11] This would imply a change in the level of the age variable. In practice, this is of secondary concern for most of our specifications because we control for artist fixed effects, and the coefficient on A will be estimated only from the within artist variations in age.

Venue capacity (K) is defined as the number of seats available for a concert. K may vary from venue to venue, but also from concert to concert in the same venue (as will be seen in the discussion of Table 1 Panel 5) because the capacity available for a given event depends on the interaction between stage design (playing in front of the audience versus a 360º stage) and the physical space of the venue.

Panel 1 in Table 1 presents summary statistics on our two explanatory variables and shows that there is much variability in artist age and venue capacity in our sample. The mean

[11] The empirical literature on the psychology of music has used different variables to measure the artist's peak influence on preferences (for example, a first hit single and best selling song). These variables are highly correlated with one another and with the age of the artist. In our sample, the correlation between the artist's age and the act's age (the time since the act or band was formed) is 0.87.

age across all concerts is 43 years, with a standard deviation of 11 years. The mean venue size is 13,000 seats with a standard deviation of 8,800. Panels 2-5 document variations in age and capacity variables when holding artist, city, city-year and venue constant; these are the control variables to be included in X as we explain shortly. Consider Panel 2 on artists. We observe an average of 275 concerts per artist. We observe artists for a relatively long period (the average difference between the first and last concert by a given artist is 11 years), as required in order to test our prediction on age holding artist characteristics constant.[12] The standard deviation of capacity for a given artist is 12,000 seats, approximately 97 percent of the average capacity in our sample. Panels 3-5 reveal that there is also significant variability in artist age and venue capacity when one looks at a given city, a given city in a given year, and even a given venue. Of particular interest, we observe an average of about 53 different concerts in the same venue, with substantial variations in available capacity (Panel 5). We can leverage this feature to test H1 at the venue level.

4-Empirical strategy and results

Figures 1 and 2 respectively plot the average frequency of price discrimination against venue capacity and artist's age. Averages are computed for intervals of 1,000 seats for venue capacity and one year for artist's age. These two figures show that the frequency of price discrimination increases with venue size (K) and with age (A). These findings are consistent with hypotheses H1 and H2, respectively. However, A and K could be correlated with other characteristics that also affect the use of price discrimination.

A test of our hypothesis should involve a set of variables X, such that holding X constant, variations in A and K are independent of any other variable that also influences the decision

[12] In addition, artists play in different years (starting date, ending date, and years off vary across artists), implying that we can control for time trends in the use of price discrimination.

to price discriminate. If this is the case, the omitted variable problem discussed earlier will not bias the inference. Consider first the issue of the artist's age. One could argue that the artists who are older on average in our sample play different styles of music or appeal to different audiences. H2 may not hold across artists due to unobserved heterogeneity at the artist level. By controlling for artist fixed effects, we can test H2 at the artist level. We test whether a given artist, performing at different stages in her career, is more likely to price discriminate when she is older. Still, one may argue that older artists sing in different cities, to leverage changes in their fan base. The endogeneity in the choice of markets that are served can be controlled for by controlling for city fixed effects. Another concern is that artist age is correlated with time, and the amount of price discrimination has changed over time (Connolly and Kruger, 2006). Introducing a time trend in X eliminates this concern.

Consider the issue of venue size (H1). As argued above, we should control for city fixed effects to account for possible endogeneity in city choice. One may argue that there are also some unobserved venue characteristics that lower the cost of implementing price discrimination (the existence of well-defined seating sections) and that are correlated with venue size. Alternatively, larger venues may be located in areas (within a city) that exclude some audience members, due to transportation constraints. To control for such unobserved venue heterogeneity, we control for venue fixed effects, which is possible because the capacity available at a given venue varies across concerts.

Estimation results: tests of H1 and H2

We estimate the impact of age and venue size on the probability of observing price discrimination using a linear probability model.

$$PD_i=\alpha_0+ \alpha_1 A_i+ \alpha_2 K_i+ X_i\alpha_3+\Phi_i\alpha_4+\varepsilon_i \qquad (3)$$

where PD_i is equal to one if price discrimination is used and zero otherwise; X_i is a vector of control variables; Φ_i is a vector including a combination of artist, city, year, and venue indicator variables (dummies) to control for unobserved heterogeneity; and ε_i is the idiosyncratic error term for concert i, such that $E(\varepsilon|A, K, X, \Phi)=0$. The results are not affected when we estimate specification (3) using a logit model (the logit marginal effects are reported in the appendix).

The first three columns in Table 2 correspond to different specifications with different sets of dummies in Φ. Column 1, which does not include any additional control variables, shows that our two main variables, artist age and venue capacity, still have a positive impact on the probability to price discriminate after we allow for correlation between the two variables. In addition, it shows that the effect is statistically significant.

In column 2, we add artist dummies, and the magnitude of the artist age coefficient increases. This suggests that the within-artist response to age is greater than the across-artist response. Adding the city dummies in column 3 does not change the coefficient on artist age, but it does reduce the coefficient on venue capacity. This is consistent with the conjecture that larger venues are located in larger cities with more heterogeneous populations and thus greater resort to price discrimination. Still, the coefficient on venue capacity remains positive and significant, as predicted under H1. In column 4, we consider the possibility of artist specific local demands by adding artist-city dummies. The main conclusions are unaffected.

Table 2, column 5 replaces the city dummies with venue dummies to control for unobserved venue heterogeneity in addition to local market heterogeneity. Variation in capacity within a given venue is driven by the interaction between the stage design and the venue characteristics. For example, an artist who plays at the center of the stadium (360°) typically has to eliminate more seats than an artist who plays with a more conventional stage design. Such choices depend on the artist's preferences and constraints dictated by the characteristics of the venue. This interaction at the stage-venue level generates exogenous variability in the number of seats that can actually be used in each venue. We restrict to a sub-sample of venues with a large standard deviation in venue size (at least 25 percent of the mean venue capacity). The coefficient on venue size does not change, suggesting that our previous results were not driven by unobserved venue heterogeneity.

Time trend

Systematic changes over time in the use of price discrimination may have taken place during our sample period. In table 3 column 1, we add a linear time trend in addition to city dummies. The two coefficients of interests do not change, but the coefficient on artist age decreases. In addition, the coefficient of the time trend is positive and significant.[13] We also consider the possibility of city specific time trends in column 2, but the results are unaffected.

A concern with these specifications is that we cannot include artist dummies. If we did so, we would not be able to separately identify the time trend and the effect of artist ageing (because these two variables and artist dummies are multi-collinear). However, note that the introduction of artist dummies in Table 2, column 2 increased rather than reduced the impact of artist age. This suggests that, if anything, artist unobserved heterogeneity may bias the estimate of ageing downwards. Unfortunately, there is no definitive solution to this identification problem. Nonetheless, we can make some progress by pursuing two strategies.

First, note that the issue of time trend cannot bias the estimate of the venue size (K) effect. In fact, having both artist dummies and the ageing effect implies that these two set of coefficients control for the possible existence of a time trend. We can even show that non-

[13] Connolly and Krueger (2006) show that the percentage of concerts charging uniform prices for all seats fell between 1980 and 2000, but they do not control for artist age or for artist fixed effects, and focus on the subset of concerts with 25,000 seats or more; a subset that is largely under-represented in our sample.

linear time effects do not affect our inference, by including artist and year dummies (Table 3, column 3). The coefficient for venue capacity does not change and remains significant.

Second, we look for the existence of non-linear effects of age. Although the linear component of the age variable cannot be separately identified from a time trend once we control for artist fixed effects, we can still separately identify its non-linear component. The objective is no longer that of measuring the impact of ageing on the use of price discrimination, but rather of testing whether ageing affects the probability of price discrimination in a non-linear fashion.

There are two ways to motivate this approach. First, we can test for the existence of any non-linear age effect, suspending judgment concerning the relationship between A and the likelihood to price discriminate. Demonstrating the existence of non-linearities shows that A matters, as predicted by H2. Second, we can go back to the theoretical model and derive a prediction on the second derivative of the likelihood to price discriminate with respect to A. The basic intuition is that the probability to price discriminate is bounded from above, so the increasing relationship has to be concave for some values of A. In addition, we speculate that the impact of age on the probability to price discriminate is highest for relatively young artists, and then decreases with age because the largest increase in heterogeneity of fans is likely related to entry of an artist's audience into the labor force.

In Table 3, column 4, we add the age of the artist squared to the specification used in column 3. The coefficient of age squared is significantly different from zero at conventional confidence levels, suggesting the existence of non-linearities. In addition, the coefficient is negative, which is consistent with the hypothesis that the marginal impact of age is decreasing. In the next subsection, we allow for general non-linear specifications and show that the concavity of the relation is robust.

Non-linear specifications

We investigate in greater detail the possibility of non-linearities in the impact of artist age and venue size on the probability to price discriminate. We respectively classify the data into 11 groups based on venue size and 9 groups according to the age of the main artist.[14] We then create one indicator variables for each group and replace the variables measuring age and venue size with these indicator variables in our linear probability model, including artist, city and year dummies (the excluded groups are for ages under 20, for capacity between 0 and 2,000 seats, and for the year 1992). Because the model is fully saturated (it includes only dummy variables for mutually exclusive groups for age, venue size, artist, city and year), there is no loss of generality using a linear probability model instead of a non-linear model such as the logit. In fact, the predicted probabilities are simply the average frequency of price discrimination for each combination of the dummy variables and cannot be outside the unit interval. Figure 3 and 4 plot the estimated coefficients, which are also reported in Table 4, column 1.

Figure 3 shows that the linear specifications in Table 2 and 3 do not conceal decreasing relations over significant intervals of venue capacity, even after controlling for the time trend. Figure 4 shows that the age of the artist has an impact on the probability to price discriminate after controlling for year fixed effects (this includes the possibility of a linear trend in the adoption of price discrimination). The coefficients for the age categories are all significantly different from zero at 10 percent confidence interval, with the exception of the age interval above 55, and jointly different from zero at conventional levels. The greatest marginal impact of age is very early in the career of an artist, between the "under 20" and the "20-25 years of age" categories. The probability to price discriminate is highest between the ages of 45 and

[14] Each age group covers five years, from 20 to 55, plus two additional category for artists younger than 20 and older than 55. Venue size groups cover 2,000 seats each, from 0 to 20,000, plus an additional category for capacity larger than 20,000 seats.

50, with a small decline for the last category, 55 and up. This relation is generally consistent with the increasing and concave relation identified in the previous table.

Additional robustness

One concern is that our age variable may reflect other trends related to the artist life-cycle. One may argue, for example, that older artists acquire experience with their audience and learn how to price discriminate over time.[15] Artists may sell to the same consumers throughout their careers (no change in valuation heterogeneity) and still price discriminate only when they get older because they then know more about their audience composition. Since experience is correlated with age, it could bias our inference about the relation between age and the use of price discrimination.

Under the experience interpretation, however, artists would be more likely to price discriminate in markets where they have played more in the recent past. Holding experience constant, proxied by the number of concerts offered in a market in the past five years, for example, we can measure the impact of age on the probability to price discriminate. In Table 4, column 2, we include in the regression the number of concerts performed by the same band in the same city in the previous 5 years and the coefficient on artist age does not change relative to Table 2 column 3. The experience variable has a negative impact on the probability of price discrimination, but this result is driven by a small number of observations with large value for experience. If one drops the one percent of observations with larger values of the experience variable, the results are not significant. This suggests that, in general, local experience with one's audience does not significantly influence the decision to price discriminate.

[15] A related point is that concerts are experience goods and that, over time, fans learn how interested they are in a band. The amount of heterogeneity in valuation increases with the artist's past playing frequency.

There may be other changes that take place over the artist's life-cycle that affect the heterogeneity of the audience and thus the decision to price discriminate. For example, systematic changes in the artist's repertoire could have an independent impact on audience composition. We cannot exclude that such changes also contribute to the relationship between artist age and the likelihood to use price discrimination.

Economics significance

Venue capacity can have a significant impact on the likelihood to use price discrimination in our sample. For example, the non-linear estimate (presented in Figure 3), suggests that moving from a 5,000 seat venue to an 18,000 seat venue increases the probability to price discriminate by 13 percent. Using the more conservative coefficient from the linear model (0.003 in Table 2, column 3 and Table 3) suggests an increase of about 4 percent.

We find evidence that ageing influences the decision to price discriminate. We cannot, however, measure the linear impact of ageing unless we make some assumption on the type of unobserved heterogeneity that may be present. Under the assumption that there is no time trend, an upper bound is that the probability to price discriminate increases by 25 percent every 10 years (Table 2). Assuming that there is a time trend, but excluding the possibility for artists' unobserved heterogeneity, gives an estimate of 8 percent (Table 3).

4-Summary

This paper uses a large dataset on concerts for popular music to investigate whether sellers are more likely to use 2^{nd} degree price discrimination when it is more profitable to do so. The theory predicts that older artists and artists performing in larger venues should be more likely to price discriminate. The intuition is that larger venues imply greater differential in product quality and older artists face older audiences with more diverse age distribution (both young and old audience members). The evidence shows that venue capacity and artist age increase the probability of using price discrimination as predicted by the theory.

This study leaves several questions for future research. First, it would be interesting to review the trend in the use of price discrimination by measuring changes in the magnitude of price discrimination. One way to measure the intensity of price discrimination would be to use the difference between the maximum and minimum prices for a given concert, as in Connolly and Kruger (2006). Second, although most artists use just one or two seating categories, some artists use three or even four. Investigating what determines the number of seating categories raises new theoretical and econometric issues that are beyond the scope of this paper.

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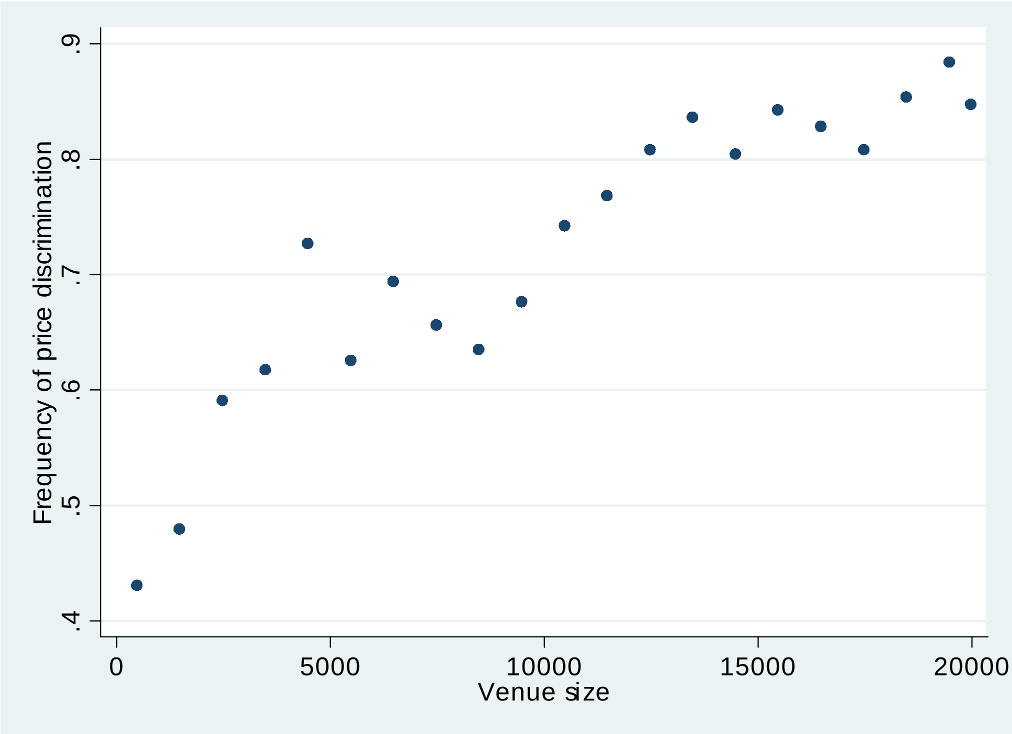
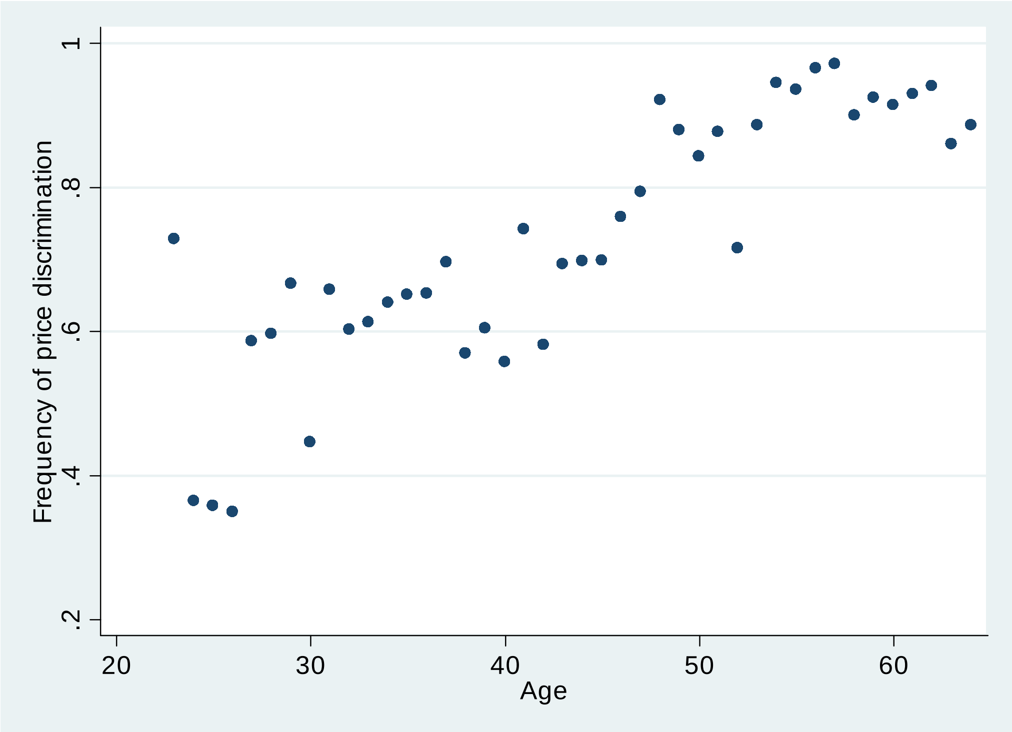
Figure 1. The frequency of price discrimination by venue size



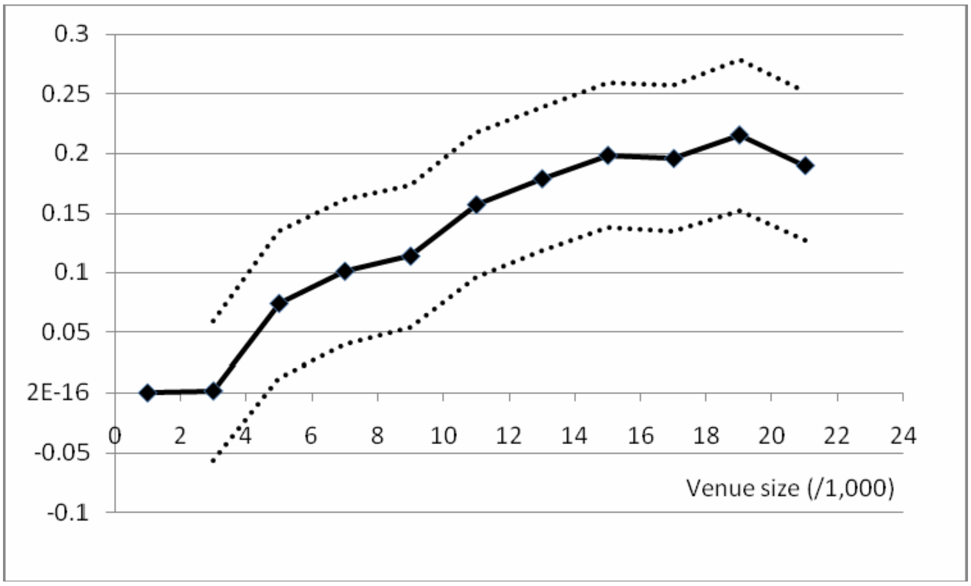
Note: venue size is reported on the horizontal axis. Data grouped by venue size, intervals of 1,000 seats up to 19,000; then 20,000 and larger.

Figure 2. Frequency of price discrimination by age of the main artist



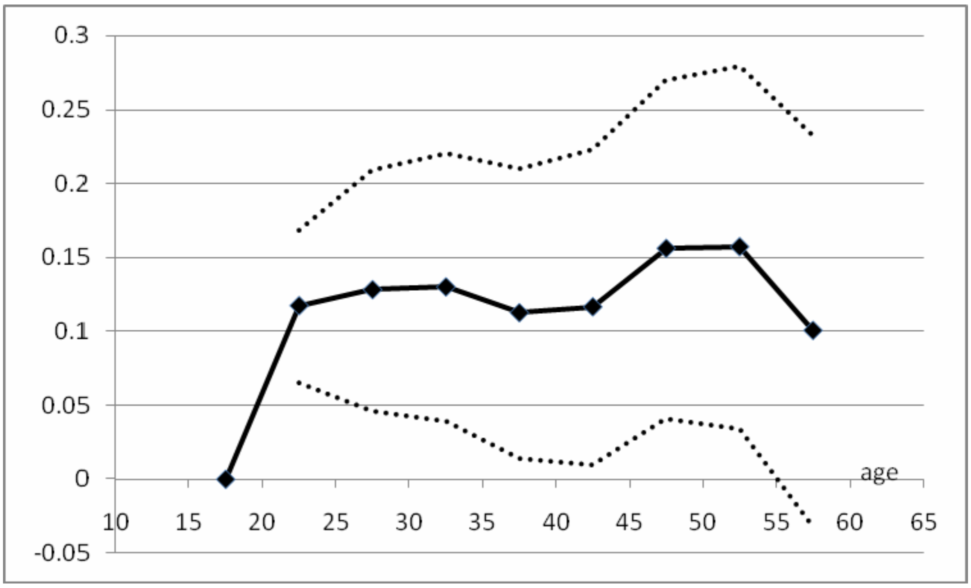
Note: Age of the artist is reported on the horizontal axis. Concerts with artist younger than 23 are grouped in one category.

Figure 3: The impact of venue size on the probability of price discrimination, controlling for artist, city and year fixed effects.



Note: the figure reports the estimated coefficients of a linear probability model with indicator variables for 10 venue size brackets (and a 90 percent confidence interval). The model also includes indicator variables for 8 age brackets, artist, city and year dummies. Each age group covers 2,000 seat intervals, 0 to 20,000 seats, plus one additional category for venues larger than 20,000. On the horizontal axis we report the midpoint of the interval for each category. The omitted category is for venue size between 0 and 2,000. Venues larger than 20,000 are grouped together and assigned a value of 22,000.

Figure 4: The impact of age on the probability of price discrimination, controlling for artist, city and year fixed effects.



Note: the figure reports the estimated coefficients of a linear probability model with indicator variables for 8 age brackets (and 90 percent confidence interval). The model also includes indicator variables for 10 venue size brackets, artist, city and year dummies. Each age group covers five-year intervals from 20 to 55, plus two additional categories for artists under 20 and over 55. The midpoint of the interval for each category is reported on the horizontal axis. The over-55 category is assigned a value of 57.5. The under-20 category (omitted in the regression) is assigned a value of 17.5.

Table 1. Variability in the age of the artist and venue capacity within artist, city, year, venue and artist-city pairs (18,285 observations).

	mean	sd	p10	p25	p50	p75	p90
Overall Sample							
Age of the artist	43	11	29	35	43	51	56
Size of the venue	12,988	8,895	3,436	7,131	12,037	17,016	20,236
Within-artist variability							
Number of observations for each artist	275	135	126	184	260	339	396
Career length (Max age - min age)	11	3	6	11	12	13	13
Capacity- (mean capacity)	0	12,576	-9,139	-5,612	-1,943	3,198	10,101
Within-city variability							
Number of observations	128	91	19	57	112	186	270
Age - (mean age)	0	10	-14	-8	1	8	13
Capacity - (mean capacity)	0	12,576	-9,139	-5,612	-1,943	3,198	10,101
Within-city-year variability							
Number of observations	11	8	2	5	9	15	20
Age – (mean age)	0	9	-12	-6	0	7	12
Capacity – (mean capacity)	0	11,688	-9,214	-3,852	-144	1,578	6,602
Within-venue variability							
Number of observations	53	45	5	17	43	78	113
Age – (mean age)	0	10	-13	-7	0	7	12
Capacity – (mean capacity)	0	9,418	-6,013	-2,598	-437	796	3,986

Table 2. The impact of the age of the artist and size of the venue on price discrimination (linear probability model)

	(1)	(2)	(3)	(4)	(5)
Artist's age	0.011***	0.024***	0.023***	0.021***	0.023***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.004)
Venue size (/1,000)	0.0058***	0.0072***	0.0031***	0.0037***	0.003*
	(0.0014)	(0.0016)	(0.0012)	(0.0015)	(0.002)
Artist f.e.?		Yes	Yes	Yes	Yes
City f.e.?			Yes	Yes	
Artist-City f.e.?				Yes	
Venue f.e.?					Yes
Observations	18,285	18,285	18,285	18,285	4,483
R-squared	0.09	0.30	0.40	0.74	0.55

Note: The dependent variable is equal to one if more than one price category is used and otherwise equal to zero. In column 5, we consider only venues whose standard deviation of venue capacity is at least 25 percent of the mean capacity of the venue. In column 4 we include dummy variables for pairs of artists and cities. Robust standard errors in parentheses, clustered by venue. The logit marginal effects are reported in the appendix. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3. The impact of the age of the artist and size of the venue on price discrimination: additional results (linear probability model)

	(1)	(2)	(3)	(4)
Artist's age	0.0088***	0.008***		
	(0.0004)	(0.0004)		
Venue size (/1,000)	0.0023**	0.0029***	0.0031***	0.0027**
	(0.0010)	(0.0010)	(0.0012)	(0.0012)
Year	0.0177***			
	(0.0015)			
Artist's age squared				-0.000302***
				(0.000063)
Artist f.e.?			Yes	Yes
City f.e.?	Yes	Yes	Yes	Yes
Year f.e.?			Yes	Yes
City specific trend?		Yes		
Observations	18,285	18,285	18,285	18,285
R-squared	0.38	0.30	0.41	0.41

Note: The dependent variable is equal to one if more than one price category is used and otherwise equal to zero. The variable Year takes integer values between 1992 and 2005. When a city specific trend is included, we add the interactions between Year and the city dummy variables. Robust standard errors are in parentheses, clustered by venue. The logit marginal effects are reported in the appendix. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4. The impact of the age of the artist and size of the venue on price discrimination: controlling for previous experience and semi-parametric specification (linear probability model)

	(1)	(2)
Artist's age		0.024***
		(0.002)
Venue size (/1,000)		0.002
		(0.002)
Number of concerts by the same band in the same city (in previous 5 years)		-0.002***
		(0.004)
Artist's age squared		
Age 20-25	0.117***	
	(0.031)	
Age 25-30	0.128**	
	(0.050)	
Age 30-35	0.130**	
	(0.055)	
Age 35-40	0.112*	
	(0.060)	
Age 40-45	0.116*	
	(0.065)	
Age 45-50	0.156**	
	(0.070)	
Age 50-55	0.157**	
	(0.074)	
Age 55 plus	0.100	
	(0.081)	
Venue size 2,000-4,000	0.002	
	(0.035)	
Venue size 4,000-6,000	0.074**	
	(0.037)	
Venue size 6,000-8,000	0.101***	
	(0.037)	
Venue size 8,000-10,000	0.114***	
	(0.036)	
Venue size 10,000-12,000	0.157***	
	(0.037)	
Venue size 12,000-14,000	0.179***	
	(0.037)	
Venue size 14,000-16,000	0.198***	
	(0.037)	
Venue size 16,000-18,000	0.196***	
	(0.037)	
Venue size 18,000-20,000	0.215***	
	(0.038)	
Venue size 20,000 plus	0.190***	
	(0.038)	
Artist f.e.?	Yes	Yes
City f.e.?	Yes	Yes
Year f.e.?	Yes	
Observations	18,285	12,512
R-squared	0.43	0.42

Note: The dependent variable is equal to one if more than one price category is used and otherwise equal to zero. In column 1, we include dummy variables for 8 intervals of the age variable, and 10 dummy variables for venue size. The estimated coefficients and the 90 percent confidence intervals are reported in Figure 3-4. In column 2, we only consider concerts after 1996. Robust standard errors in parentheses, clustered by venue. * significant at 10%; ** significant at 5%; *** significant at 1%.

APPENDIX

Table A1. The impact of the age of the artist and size of the venue on price discrimination (logit marginal effects)

	(1)	(2)	(3)	(4)	(5)
Artist's age	0.011***	0.025***	0.023***	0.069***	0.028***
	(0.000)	(0.002)	(0.001)	(0.005)	(0.004)
Venue size (/1,000)	0.007***	0.007***	0.002**	0.0068**	0.0037*
	(0.002)	(0.002)	(0.001)	(0.0037)	(0.0023)
Artist f.e.?		Yes	Yes	Yes	Yes
City f.e.?			Yes	Yes	
Artist-City f.e.?				Yes	
Venue f.e.?					Yes

Note: Robust standard errors in parentheses, clustered by venue. In column 5, we consider only venues whose standard deviation of venue capacity is at least 25 percent of the mean capacity of the venue. Marginal effects computed at the mean of the independent variables. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A2. Additional results (logit marginal effects)

	(1)	(2)	(3)	(4)
Artist's age	0.009***	0.0090***		0.021***
	(0.0004)	(0.0004)		(0.002)
Venue size (/1,000)	0.002**	0.0020***	0.0024***	0.002*
	(0.001)	(0.0010)	(0.0010)	(0.001)
Year	0.018***			
	(0.0013)			
Number of concerts by the same band in the same city (in previous 5 years)				0.002
				(0.003)
Artist's age squared				
Artist f.e.?			Yes	Yes
City f.e.?	Yes	Yes	Yes	Yes
Year f.e.?			Yes	
City specific trend?		Yes		

Note: Robust standard errors in parentheses, clustered by venue. Marginal effects computed at the mean of the independent variables. * significant at 10%; ** significant at 5%; *** significant at 1%.