The Impact of Price Discrimination on Revenue: Evidence from the Concert Industry

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Abstract: Concert tickets can either be sold at the same price or at different prices reflecting different seating categories. Price discrimination generates about 5 percent greater revenues than single-price ticketing. The return to price discrimination is higher in markets with greater demand heterogeneity, as predicted by price discrimination theory. The return to an increase from three to four concert seat categories is roughly half that of an increase from one to two.

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1-Introduction

Although price discrimination is widely discussed in the economic literature, much less has been published in the way of empirical evidence documenting its impact on revenues. Some headway in filling this gap has been made in recent years, with studies focusing on single firms (Leslie, 2004) and single markets (McManus, 2008). Here we report the first systematic evidence of a relationship between price discrimination and revenue, basing our analysis on a rich panel dataset of pop music concerts covering a large share of the US concert industry over multiple years.

Pop concert ticket pricing provides a unique context for the study of price discrimination, not least of which because it is virtually a textbook application of the theory. The seating capacity and the distribution of seat quality are given, and the only issue is whether to sell different seats at the same or at different prices. In most other studies in the literature, price differences among products might be related to variations in marginal cost, not just to price discrimination (Shepard 1991, Clerides 2004). The concert industry offers the additional advantage of having relatively straightforward pricing strategies. A concert may offer all seats at the same price (single-price ticketing), or split seats in seating categories, each with its own price. In this paper, we say that a concert uses price discrimination whenever there are at least two categories of seats and prices.

Our dataset covers more than 21,000 concerts by the top 100 grossing artists in the concert industry over the period 1992-2005.[3] For each concert in our sample, we have access to information not only about pricing policies, as have past non-structural studies of price discrimination (e.g., Shepard 1991, Nevo and Wolfram 2002, Busse and Rysman, 2004), but also about revenue. We can thus investigate how the former influences the

[3] If we increased the sample to include the top 500 grossing artists over the same period, for example, the top 100 artists would represent 70 percent of total revenue.

latter. Finally, we also have information on the characteristics of demand (features of the local population).

We pursue two strategies for investigating the relation between price discrimination and revenue. First, we estimate the impact of price discrimination on revenue by using a fixed effects panel data approach to exploit the richness of our data. The main challenge in interpreting the results is the issue of unobserved demand heterogeneity. Demand varies from concert to concert, and the demand shifters that influence the level of revenue may be correlated with the decision to price discriminate. We follow the approach proposed by Nevo and Wolfram (2002), who suggested that fixed effects be included to control for local demand, product, and year. We do so by considering city, artist, and year fixed effects. The city where the concert takes place captures how demand depends on the local audience. The artist captures the specific demand for a given product. The year of the concert captures changes over time in preferences or technology. In addition to these fixed effects, we can also control for tour fixed effects (which more narrowly describe the product than artist) and venue fixed effects (which capture characteristics of both the product and the local public). We also know who the promoter is for each concert. This is important because the promoter's actions may influence both revenue and the decision to price discriminate. We can also include a number of fixed effects for pair wise interactions (e.g., artist-city, city-year, and artist-year) and still identify the impact of price discrimination, because different artists play in different cities in different years.

There are two ways to read this analysis. First of all, our approach is of descriptive interest in itself. We show that unobserved demand heterogeneity can introduce significant biases in the estimated return of price discrimination. We show that this is relevant for the unobserved characteristics of artists, cities and years. The return to price discrimination decreases sharply when we include these fixed effects. This is not surprising, as artists and cities with larger revenues are also more likely to use price discrimination. Moreover, average concert revenue and the average frequency of price discrimination have increased over time. However, the inclusion of the promoter, venue or tour fixed effects does not change the estimated return to price discrimination, which remains stable at around 5 percent. The estimated return still does not change when we add fixed effects for pair wise interactions. We conclude that unobserved demand heterogeneity is only relevant at a coarse level of aggregation.

Another way to read the evidence is to interpret the estimated impact of price discrimination as causal. This is the correct interpretation if there is no omitted variable that is correlated both with price discrimination and revenue after controlling for artist, city, and year fixed effects. We can make a case for this assumption. In fact, we experiment with fixed effects that control for many economic variables that could generate endogeneity, and none prove to matter. Since the estimated coefficient on price discrimination remains stable at around 5 percent, we are fairly confident that additional unobserved heterogeneity is not a concern.

A second approach to establishing causality is to examine the theoretical mechanism through which price discrimination influences revenue. This provides a completely new way of looking at the evidence. We study how the return to price discrimination depends on demand characteristics. Building upon Rosen and Rosenfield's (1997) model of ticket pricing, we show that the return to price discrimination is expected to increase with intra- and inter-personal differences in willingness to pay for seat quality. These specific predictions of price discrimination theory can be tested. This approach is interesting for two reasons. First, it allows us to seek evidence of a specific causal mechanism of price discrimination on revenues. Second, we can measure the magnitude of the impact of demand characteristics on the return to price discrimination.

If seat quality is a normal good, intra-personal differences in willingness to pay for seats in different categories should increase with income. As predicted, we find that the return to price discrimination increases with city average income. We also find that the return to price discrimination is higher in markets with greater inter-personal differences in willingness to pay. For example, the return is higher in larger markets or in markets where the local public is more heterogeneous in terms of ethnicity and type of occupation. The consistency of this second set of results with standard economic theory corroborates our interpretation of the initial results.[4]

Finally, we tackle the question of how revenue changes when the number of product categories increases. We compare the impact of offering 2, 3, and 4 product categories and show that the marginal impact of additional categories is decreasing with the number of seating categories made available. These results contribute to the literature on the return to complex product portfolios (Wilson 1993, Miravete 2007).

Our evidence contributes to previous studies of price discrimination (Shepard 1991, Nevo and Wolfram 2002, Busse and Rysman 2005). In contrast with those earlier investigations, we select an industry where price differentiation is unambiguously due to price discrimination and investigate the relationship between price discrimination and revenue. Our results complement evidence deriving from the estimation of structural models (Leslie 2004, Miravete and Röller 2004, McManus 2008). Our industry is most closely related to the firm studied in Leslie, and the magnitude of our estimates is consistent with the results presented in his simulations. There are important differences, however. The two studies adopt very different methodologies that leverage different

[4]These results diverge from those of previous empirical studies, which have rejected some theoretical predictions of monopoly models of price discrimination (Verboven 1999, Nevo and Wolfram 2002). A candidate explanation is that these past studies considered oligopolistic industries, whereas our application more closely matches the standard case of monopoly pricing.

sources of variations in pricing policies. We compare events with and without price discrimination, which is not possible in Leslie's analysis because the seller always uses two or three seating categories. Instead, Leslie first estimates a demand system (leveraging variations over time in the level of price and in the allocation of seats to categories) and then simulates the return to price discrimination. In addition, we can measure how market characteristics influence the return to price discrimination exploiting variability across a large number of markets. Finally, our work also contributes to the empirical literature on cultural economics (Krueger 2005 and Huntington 1993) and is related to the theoretical literature on ticket pricing (Rosen and Rosenfield 1997 and Courty 2003).

The rest of this paper is organized as follows. First, we introduce the concert tour industry and present our data. Section 3 introduces the econometric framework and discusses the issue of causality. Section 4 presents the results, and Section 5 concludes.

2-Concert Tour Industry: Data, Definitions, and Stylized Facts

The modern concert tour industry was born in the late 1960s when a few bands such as the Rolling Stones and Led Zeppelin regularly started touring a variety of arenas and stadiums, using their own experienced crew for the sound, staging and lighting. In the 1980s, advances in technology allowed bands to offer even more ambitious stage shows that were louder, flashier, and available to ever-growing audiences. By 2007, the North American concert industry had grown to $4 billion in revenue and 100 million in attendance.[5]

Most of the concerts in our sample (19,540 concerts out of 21,120) formed part of a tour. In brief, a concert tour is typically organized by an artist represented by his or her manager, a (booking) agent, and a promoter. The artist and the agent agree on an act and a tour plan.

[5] The information on the touring industry presented in this section was collected by interviewing concert promoters as well as two professors teaching courses on concert promotion. Some of the information was also drawn from recent books and industry manuals on concert promotion, in particular Waddell et al. (2007).

The agent then looks for promoters to organize the event in each city. The artist comes to an agreement with each promoter on a pricing policy and on a revenue sharing rule. Promoters are in charge of organizing the events, which involves booking venues, advertising, and collecting revenues. Our data identifies the main parties involved in organizing a concert (artists, venue, and promoter), with the exception of the agent, whose role is limited to putting artists and promoters in touch. There are some variations on the theme. Most artists use the same set of promoters to be in charge of the tour but others also add local promoters in some cities to tap into the local expertise so crucial for success. A few artists do everything in-house and contact the venues directly. Although there are different types of tours (e.g., promotional tours of new releases, seasonal tours, festival tours), all of the concerts in a single tour usually include a common set of songs and a similar stage, and are marketed together.

Each event is unique and there is no set formula for deciding whether to price discriminate and for setting prices. Ticket prices are typically determined when the tour is announced and do not change.[6] As a consequence, there is no second chance if one gets the wrong number of seating categories or prices. Artists and promoters vary in their ability and/or willingness to design complex pricing policies.

2-1 Data

This study focuses on the primary market for concert tickets, with data from two main sources. The core of the data was collected by *Billboard* magazine and contains variables similar to those used by Connolly and Krueger (2006). For each concert defined by a date, venue, and artist(s), we observe the promoter in charge, the different prices offered, the total capacity, and the attendance and revenue realized. Table 1 presents summary statistics for the main variables. In addition, we collected tour dates from band and fan websites and

[6] Promoters may add or cancel events, but rarely change prices or category allocation.

information regarding the bands from music websites, artist websites and the Rolling Stone Encyclopedia of Rock and Roll.

Our resulting panel data is thus three-dimensional. The first dimension describes the product, i.e., a concert, and can be aggregated by music genre, artist, or tour. The second dimension describes local demand and can be aggregated at the level of city or state.[7] In addition, knowledge of the venue in which the concert takes place provides information about both product and demand characteristics. The third dimension is time.

There are several differences from the Connolly and Krueger (2006) dataset. In terms of breadth, we focus on the top 100 grossing artists over the period 1992-2005, which represents the majority of the industry (see footnote 3). In terms of depth, our data is richer in several dimensions. First, we observe all of the prices for each concert, rather than just the highest and lowest prices. Second, we know whether a concert is part of a tour and, if so, to which tour it belongs. This additional information allows us to provide a much more complete picture of the pricing strategies across seating categories at the tour level.

2-2 Definitions, Stylized Facts, and Sources of Variation in Price Discrimination

In our sample, 56 percent of the concerts offer two price categories, 25 percent one, 15 percent three, and the remaining 4 percent four categories. We say that a seller price discriminates if tickets are sold at more than one price. This definition of price discrimination distinguishes between unsophisticated pricing (general admission or single price ticketing) and sophisticated pricing (differentiated seating). While this broad distinction is the focus of most of this paper, Section 4.5 computes the return to each

[7] We also collected data on local market characteristics from the 2000 Census. We match our dataset on concerts with census data at the city or place level.

additional pricing category. Beyond these distinctions, we do not attempt to measure the extent of price discrimination (Clerides, 2004).[8]

Figures 1 and 2 plot the share of concerts that use price discrimination for the cities and artists with the largest number of concerts in our sample. Price discrimination varies greatly across cities and artists. There is a general trend toward greater use of price discrimination (Connolly and Krueger 2006).[9] But there are also many variations on this trend, as well as notable exceptions.[10]

A linear probability model explaining the existence of price discrimination with artist, year, and city fixed effects accounts for 52 percent of the variability in the use of price discrimination.[11] This figure is consistent with the hypothesis that the choice to price discriminate depends on product and demand characteristics, but it also indicates that these fixed effects cannot explain about half of the variations in the use of price discrimination. Even if we only consider the concerts by a single artist in a given year, there is still significant variability in the use of price discrimination. Only 27 percent of the 846 artist-year combinations with more than two concerts consistently used price discrimination, or never used price discrimination, but never did both. Similarly, we find significant heterogeneity in the use of price discrimination when we restrict the sample to artists performing repeatedly in the same city, artists repeatedly hiring the same promoter,

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[8] For example, two pricing policies with the same number of categories and the same prices are classified as equally discriminating according to our definition, despite the fact that they may allocate different proportions of seats to each category.

[9] In our sample, price discrimination roughly doubled from less than 50 percent to 90 percent from 1992 to 2005, but this figure is partly due to the age composition of the sample (older artists are over-represented late in the sample) and the fact that the artist's lifecycle influences the use of price discrimination (Courty and Pagliero 2008).

[10] 6 of the 112 cities with more than one concert both in 1992 and 2005 experienced no increase in the frequency of price discrimination. For artists, the figures are 3 out of 28 and for promoters 2 out of 18.

[11] Using finer controls (replacing artist fixed effects by tour effects, and cities by venues) increases the percentage of variations explained by only 4 percent.

concerts within the same city and year, or promoters organizing concerts in the same year, city and city-year combinations.[12] The next section explains how these sources of variation are used to estimate the impact of price discrimination on revenue.

3-Empirical Framework

We estimate variants of the following model,

$$\ln(R_i) = \gamma_0 + X_i'\gamma_1 + PD_i\,[\gamma_2 + Y_i'\gamma_3] + \Phi_i'\gamma_4 + \varepsilon_i \qquad (1)$$

where $\ln(R_i)$ is the log of revenue in concert i; γ_0 is a constant; X_i is a vector of concert characteristics affecting revenues for concert i, such as venue capacity and number of artists performing; PD_i is an indicator variable that is equal to one if more than one price category is offered but otherwise zero; Y_i is a vector of concert and local market characteristics, affecting the return to price discrimination. Φ_i is a vector of indicator variables that could include artist or tour, city or venue, promoter, year dummies, as well as interactions between them; γ_0 and γ_2 are scalars, and γ_1, γ_3 and γ_4 are vectors of parameters. The error term ε_i captures, among other things, demand shocks that are realized after prices are set and shocks to revenues resulting from matches between the act, the venue, and the local public.[13] If $E(\varepsilon|X,Y,PD,\Phi)=0$, then $\gamma_2 + Y^*\gamma_3$ is the average return to price discrimination (where Y^* denotes the sample mean of the variables in Y) and the vector γ_3 is the marginal return of the variables in Y.

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[12] Of the 2,190 pairs of artists and promoters who organized at least two concerts in the sample, only 62 percent used price discrimination all the time or never. The corresponding figure is 70 percent for the 4,831 combinations of artist and city in which an artist performed at least twice, 37 percent for the 2,570 city-year combinations, and 36 percent for the 775 promoter-year combination, 50 percent of the 2,066 promoter-city combinations and 58 percent of the 3,143 promoter-city-year combinations with at least two concerts.

[13] Demand uncertainty is a defining characteristic of the performing arts (Courty, 2003). In our sample, unsold tickets are not uncommon: the average capacity utilization is 85 percent.

The estimation problem falls within the scope of the treatment effect literature once one labels the concerts that use price discrimination as the treated ones. The artist sets PD=1 if doing so increases profits, that is, if the gain from price discrimination, $R_i(PD_i=1)$-$R_i(PD_i=0)$, is higher than the implementation cost. This cost could include, among other things, market research and costs associated to ticketing and distribution. Some of the variables that influence the decision to price discriminate may be correlated with the level of revenue R. If these variables are observed by the econometrician, then the selection into treatment can be easily managed by including the appropriate controls in X. Selection on unobservables, however, may induce a bias into the estimated return, and constitutes our main concern.

The principal sources of unobserved heterogeneity in our application are unobservable demand shifters that influence the level of demand (and therefore revenue) and the return to price discrimination (and therefore the decision to price discriminate). For example, it is possible that more popular artists may play to a more diverse audience. In this case, the positive correlation between the average willingness to pay and the heterogeneity in willingness to pay may bias upward the estimated return to price discrimination. If the popularity of an artist is fixed over time and does not vary across locations, we can solve the endogeneity problem by controlling for artist fixed effects. This approach builds on the work of Nevo and Wolfram (2002), although we can control for unobserved heterogeneity at a much finer level.

Other demand shifters may also cause selection on unobservables. We use six sets of fixed effects to control for a broad range of demand shifters that could influence demand and price discrimination: artist, city, year, venue, tour and promoter. Artist fixed effects, for example, control for any variable that varies across artists but is constant for a given city, year, venue, tour and promoter. We can also include interacted fixed effects. For example, we can control for the changes in popularity of an artist over time by using artist-year fixed effects. Doing so is of particular importance for those sets of (un-interacted) fixed effects that will be found to influence the return to price discrimination.

After controlling for demand heterogeneity in such detail, the return to price discrimination can be identified only if there is still significant variability in the use of price discrimination, and this variability is not correlated with the remaining unobserved determinants of revenue. As discussed in the previous section, the first condition is satisfied: there is still a significant amount of variability in the use of price discrimination after we control for the six sets of fixed effects or even for interactions between these fixed effects. Second, several variables may generate exogenous variability in price discrimination. In fact, the match between the stage and the venue determines the pool of seat qualities available for sale within the venue. The stage is fixed at the tour level (e.g., facing the audience versus playing 360 degrees) and it may not suit all venues equally well. This is consistent with the fact that the number of seats available in a given venue varies greatly. Because the number and type of seats that are removed varies from concert to concert, the venue-tour match influences the return to price discrimination even when holding tour and venue constant.[14] In addition, some artists and promoters may be experimenting with price discrimination.[15] Finally, the implementation costs mentioned above might vary for reasons that have nothing to do with the level of demand (e.g., an artist may have access to consumer research in some, but not all, local markets).

4-Results

[14] Clearly, the venue-tour match also influences the available capacity and thus the level of revenue, but capacity is included in X. Beyond that, there is no reason why it should influence the level of revenue.

[15] Waddell et al. (2007, p. 199) report that experimentation and innovation influence the decision as whether to use price discrimination: “every once in a while you’ll have a clever promoter in another market that comes up with an interesting idea you never thought of.”

Tables 2 and 3 restrict γ_3=0 and present estimates of the impact of price discrimination on revenue. Table 2 does not allow for interactions in the controls while Table 3 does. Table 4 reports the estimates of interaction effects γ_3.

4-1 Controlling for Unobserved Demand Heterogeneity

The first row of Table 2 reports the average increase in revenues associated with the use of more than one pricing category. Each column corresponds to a different specification: column 1 reports the results without control variables, column 2 controls for capacity, and column 3 adds artist, city and year fixed effects. Controlling for capacity reduces the impact of price discrimination by half.[16] One interpretation is that revenue is higher in larger venues, and larger venues are more likely to use price discrimination because heterogeneity in seating experience increases with size. Adding artist, city, and year fixed effects further reduces the impact of price discrimination. Again, the use of price discrimination is correlated with time trend, artist popularity, and city demand.[17] When we compare the results of the fixed effect estimator in column 3 with the corresponding random effect estimator (Hausman test), we reject the null of no change in the parameters of the remaining control variables. In fact, the return to price discrimination is significantly higher (24 percent) when fixed effects are not included than when they are (5 percent).[18] Unobserved heterogeneity amongst artists, cities and years matters.

[16] The results are robust when we also add log-capacity squared to capture non-linear capacity effects.
[17] When we add only year fixed effects along with capacity, the impact is 9 percent (not reported). This sharp drop could be explained by the simultaneous increase in revenue and use of price discrimination during our sample period as documented by Krueger (2005); however, this figure over-estimates the role of time, because age increases over the sample period and older artists earn more and are more likely to price discriminate.
[18] We also tested for the existence of unobserved heterogeneity for some of the additional fixed effects included in Tables 2 and 3. For example, we compared column 5 in Table 2, with the results of the specification column 4 with the addition of random promoter fixed effects, and rejected the equality of the coefficients common to both specifications. We cannot rule out the existence of promoter

In column 4, we replace the artist fixed effects with tour fixed effects and the city fixed effects with venue fixed effects, but the magnitude of the estimated impact of price discrimination does not change. This is a richer specification, since, on average, each artist is observed in more than 6 tours in the sample. The tour fixed effects capture common features of the event, such as the stage set and songs. It also allows for different tours attracting different audiences as well as implicitly controlling for artist fixed effects.[19] Venue fixed effects not only control for venue heterogeneity (physical constraints and location) and for the city-specific demographics but also for venue-specific characteristics, such as location, type (theater or stadium) and overall experience. The estimates of γ_2 do not change. In column 5, we add promoter fixed effects, capturing the time invariant characteristics of the promoter for each concert; this proves to have no influence on the impact of price discrimination.

To conclude, only artist, city and year fixed effects significantly influence the return to price discrimination. Once we control for these three sets of dummies, the addition of tour, venue, or promoter dummies does not change the estimated coefficient on price discrimination. Even from a descriptive standpoint, this analysis of the data constitutes a contribution by showing that unobserved demand heterogeneity across artists, cities and years greatly affects the results, whereas venue characteristics (excluding venue size for obvious reasons), tour, or promoter do not influence the return to price discrimination.

The magnitude of the impact of price discrimination is economically significant: revenues are 5 percent greater when more than one price is used, and for the average concert in 2005, this amounts to over $37,000. In 2005 alone, price discrimination accounted for over $50 million for the top 100 artists.

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unobserved heterogeneity, but such unobserved heterogeneity does not affect the economic magnitude of the estimate of the return to price discrimination.

[19] When a tour is jointly organized by two artists, we treat it as though it were organized by a different artist.

4-2 Controlling for Interacted Fixed Effects

Unobserved heterogeneity could also be present at a finer level. For example, there could be band specific time trends in demand, city specific trends in the local demand for pop concerts, or differences across cities in the demand for a given band. Such a possibility cannot be ruled out a priori. A model with a three-way interaction between artist, city and year cannot be estimated, since artists typically perform only once in each city in a given year.[20] However, we can estimate models that include fixed effects for pair wise interactions (artist-city, city-year, artist-year, …). We can still identify the impact of price discrimination because different artists play in different cities in different years and the use of price discrimination varies within sub-cells of artist-city, city-year, and artist-year (see discussion in Section 2.2)

In Table 3, column 1, we introduce a set of dummies for the interaction of artist and city fixed effects. This captures differences in preferences for bands across cities. The interaction between city-artist does not change the coefficient of price discrimination. In column 3, we include the interaction of artist and venue dummies: for each band, we allow heterogeneous consumers not only across cities, but also across venues within a city. This is an additional robustness test since we have already shown that venue dummies capture no new unobserved heterogeneity beyond that already captured by city dummies. Again, the coefficient of PD does not change. We rule out unobserved heterogeneity due to permanent characteristics of the artist and venue.

The same conclusion holds when we consider time interaction effects. A significant concern is that the adoption of price discrimination over time may be correlated with changes in demand or venue characteristics. Column 2 controls for city-year fixed effects, ruling out city heterogeneity in change in demand, and accounting for the change in the

[20] In some cases, a tour includes more than one identical show in the same location. However, these concerts are marketed together and priced identically.

number and preferences of fans within a city, as well as other time-varying city-specific characteristics.

Columns 1, 3, and 4 control for artist-year fixed effects, ruling out the possibility that the demand for different artists has changed at different points in time, due, for example, to aging of the population or changes in the artist's public. Column 4 further adds city specific linear trends to capture the within-city change in preferences and demographic variables.[21] Endogenous adoption of price discrimination correlated with time is unlikely to be driving our results. In column 5, we interact the artist and promoter indicator variables to capture the fact that pricing strategies are often jointly set by artists and promoters. Again, this is an additional robustness test since we have already shown that promoter fixed effects alone did not change the coefficient estimate in Table 2. We conclude that it seems unlikely that we have missed interaction effects influencing both PD and revenue.[22] Even after controlling for artist-city, artist-year, and city-year interactions, the impact of price discrimination is systematically positive and statistically significant at conventional levels with a value between 4 and 6 percent.

4-3 Demand Heterogeneity and the Return to Price Discrimination

We now focus on one mechanism through which price discrimination is expected to lead to higher revenues: price discrimination allows increasing revenues more when demand heterogeneity increases. This is a general prediction of price discrimination theory, but it is

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[21] At this point, the addition of city-year fixed effects would reduce the degrees of freedom too much.

[22] $E(\varepsilon|X,PD,\Phi)=0$ could be violated if there is an observed component of the return to price discrimination that varies across concerts and affects the decision to price discriminate. Assume the treatment effect has an independent random component α (e.g., concert-specific feature of local demand) that is observed by the seller but not by the econometrician, so that $\gamma'_2=\gamma_2+\alpha$, and the seller chooses whether to price discriminate on the basis of this information. When the return to price discrimination is random, estimating model (1) by OLS provides the average treatment effect on the treated $\gamma'_2=\gamma_2+E(\alpha_i|PD=1)$, not the average treatment effect γ_2 (Heckman and Robb, 1985). Even in this case, the estimated return to PD is still a pertinent measure of the return to price discrimination.

particularly relevant in the concert industry, because the marginal cost is zero, and physical constraints dictate the quality and quantity of seats available in the venue.[23] This prediction can be illustrated using three simple examples, within the framework of Rosen and Rosenfeld (1997).

Assume for simplicity that the venue can be split into just two seating categories. There are n_s seats of quality s, s=l,h. There is a large number of identical consumers willing to pay v_s for a seat of quality s with $v_h > v_l$. Valuations are known to the seller. In this case, the seller can extract the entire surplus and the return to price discrimination increases with the consumer's willingness to pay for an upgrade to a high quality seat, $[R(PD=1)-R(PD=0)]/R(PD=0)=[(v_h/v_l)-1][n_h/(n_h+n_l)]$. Taste for quality (intra-personal differences in valuation) influences the return to price discrimination. A larger ratio between the valuation for high and low quality seats implies a higher return to price discrimination.

A second model accounts for the fact that different consumers typically sit in different sections. Consider a simple extension with two types of consumers (θ=L,H) such that the high type buys only high quality seats. For example, the high type may prefer staying at home than seating in a low quality seat. Consumer θ values v^{θ}_s a seat of quality s=l,h with $v^H_s > v^L_s$. If there are enough high types to fill the high quality seats, but not enough to fill the entire venue (Rosen and Rosenfeld 1997), then the seller sells the high quality seats to the high types and the low quality seats to the low types, extracting the entire surplus. The return to price discrimination is now $[(v^H_h/v^L_l)-1][n_h/(n_h+n_l)]$. As before, the return increases with willingness to pay to upgrade (intra-personal difference), but the novelty is that heterogeneity across groups (inter-personal differences) now also matters, since $v^H_h/v^L_l = (v^H_h/v^H_l)(v^H_l/v^L_l)$.

[23] For example, relatively small concerts take place in concert halls, typically divided into the orchestra, mezzanine and balcony. For a given stage, the artist cannot alter the number and allocation of seats to these categories, nor eliminate seats of lower quality.

Finally, the prediction that heterogeneity in willingness to pay increases the return to price discrimination holds in a more general model of second degree price discrimination where the high type also values low quality seats. Under the standard assumption that v^H_h-v^H_l> v^L_h-v^L_l, 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 R(PD=1)=[n_l+n_h]v^L_l+n_h(v^H_h-v^H_l). Since the first term corresponds to the revenue under uniform pricing, the return to price discrimination, $[(v^H_h/v^H_l)-1](v^H_l/v^L_l)[n_h/(n_l+n_h)]$, depends again on inter- and intra-individual heterogeneity in valuation in the population.

4-4 Results on Demand Heterogeneity

We estimate model (1) including in Y proxies for heterogeneity in willingness to pay of the public (γ_3 is no longer constrained to be equal to zero). These variables are derived from the 2000 census, matching our data on concerts with census data at the city or place level. Thus, they are city specific and time invariant. We investigate how such variables influence the return to price discrimination. In other words, we focus on the interaction between PD and the characteristics of the local population in Y. Identification of γ_3 derives from the occurrence of concerts using and not using price discrimination in cities with different characteristics.

Since we are not interested in the impact of these variables on the level of revenue, we can include in Φ the same set of fixed effects as before. City fixed effects, for example, control for the impact on the level of revenue of any variable that is fixed at the city level (including our measures of heterogeneity of the public). This does not affect our ability to estimate the impact of public heterogeneity on the return to price discrimination. Table 4, column 1 reports the new estimated coefficients (including artist, city and year fixed effects as in Table 2, column 3), while columns 2 and 3 include a richer sets of fixed effects (as in Table 2, columns 4 and 5 respectively).[24]

Income level: to the extent that quality of the experience is a normal good, we expect that the difference in willingness to pay for a high or low quality ticket increases with income. So we use median household income as a proxy for the difference in valuation between the high and low quality seats, (v_h/v_l), and interact it with PD. Median household income has a positive and statistically significant impact on the return to price discrimination. A $5,000 increase in income implies a 1.5 percent increase in the return to price discrimination.

City size (population): The diversity of public preferences is likely to be higher in larger and more densely populated cities, in the sense that there are larger differences across consumers in willingness to pay for a seat of the same type (v^H/v^L). The return to price discrimination is higher for concerts that take place in larger cities.[25] A change from a median size city (200,000) like Grand Rapids (MI), to one at the 75th percentile (about 530,000) such as Portland (OR), implies a 1.5 percent higher return to price discrimination.

Ethnic diversity: We compute the Gini diversity index using three racial groups (white, black, other).[26] Table 4 shows that the return to price discrimination is higher in cities with a more ethnically diverse population. This is consistent with diversity in preferences for a given concert (v^H/v^L) being correlated with ethnic group heterogeneity. A one percent increase in the heterogeneity index implies a 0.08 percent increase in the return to price discrimination. A change from the median to 75th percentile of the heterogeneity

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[24] Overall, the average treatment effect [γ_2 +Y*γ_3], where Y* includes the mean of the variables in Y, is not significantly different from the estimates in the previous sections.

[25] City size and population density are highly correlated and capture the same aspect of heterogeneity. We find similar results when we include population density rather than city size in Y.

[26] The Gini (1912) diversity index is equal to the probability that two random individuals belong to different groups. It is computed as $G=1-\Sigma_i(f_i)^2$, where f_i is the relative frequency of observations in group *i*.

distribution implies an increase of 1.1 percent in the return to price discrimination. This corresponds to a change between Pittsburgh (PA), a city with median ethnic diversity (a white population of 68 percent), to Cincinnati (OH), which is at the 75^{th} percentile of the heterogeneity distribution (a white population of 53 percent).

Occupational diversity: We compute the Gini diversity index using data on the proportion of the population in different occupational groups (management, services, sales, farming, construction, production). The rationale for such a proxy is that preferences for music may be correlated with occupation. A city with a more mixed population is likely to display a greater range of willingness to pay for a given concert. The results in Table 4, column 1, show that a one percent increase in occupational diversity implies a 0.5 percent increase in the return to price discrimination. A change from the median to the 75th percentile in diversity implies about a 1.2 percent increase in the return to price discrimination.

Income diversity: Income heterogeneity is measured by the Gini diversity index using 16 income brackets. Greater income inequality naturally implies more heterogeneity in willingness to pay across individuals. After controlling for ethnic and occupational heterogeneity, the impact of income diversity is not significantly different from zero.

These results are important for two reasons. First, they provide direct evidence of a specific mechanism through which price discrimination affects concert revenue. If our previous results were only driven by some remaining unobserved heterogeneity, and not the causal impact of price discrimination, then there would be no reason for observing a correlation between demand heterogeneity and the return to price discrimination. Second, testing the impact of demand heterogeneity on the return to price discrimination is interesting per se, since this is an important prediction of price discrimination theory.

4-5 Return to Additional Seating Categories

The number of seating categories is relatively low in the concert tour industry. Although Leslie (2007) reports the same observation in his study of a Broadway show (his firm never uses more than three seating categories for a given show), the number of seating categories can be quite large for classical music events (Huntington, 1993). Assuming that the seller chooses the number of seating categories, one would expect to observe few seating categories if the return from adding categories is low. In fact, this is the view taken by Wilson (1996) and Miravete (2007) in the context of non-linear tariffs. They argue that the menus of tariff options offered in practice are simple because the impact on revenue from adding complexity beyond two or three tariff options is small, and arguably smaller than the associated marketing costs.

While Miravete's evidence applies to non-linear tariffs, there is no corresponding empirical study, to our knowledge, for a product line monopolist. This is despite the fact that many sellers forgo offering multiple product qualities (Anderson and Dana, 2008). Translated into the context of our case study, we would expect to find that the return to additional seating categories should be decreasing and small once a couple of categories are already offered.

In Table 5, we report the average increase in revenues associated with using multiple seating categories. We include three indicator variables, equal to one when the number of seating categories is equal to two, three and four respectively (recall that only 4 percent of the concerts in our sample offer 4 seating categories). Table 5, Columns 1 and 2 include the same control variables as in Table 2, columns 3 and 4. Table 5, column 3 includes artist-year and artist-city fixed effects as in Table 3, column 1.

The marginal impact of one additional category is positive but decreasing as the number of existing categories increases. In column 1, the average increase in revenue associated with the introduction of a second seating category is 4.6 percent. With the introduction of a third category, revenue further increases by 3.1 percent and with the fourth by only 2.1. Similar results hold for the alternative specifications, and the decline in the marginal increase in revenues is greatest for the fourth category.

Although the return to price discrimination decreases with the number of seating categories, it is still the case that the return from adding a third and fourth category is significant (about half the return of introducing a second category). This raises two questions: (a) why do some artists still not price discriminate? (b) why do the majority of artists use only two price categories?[27] The evidence suggests that artists leave money on the table, which is consistent with the observation that resale markets are to a large extent fueled by arbitrage opportunities due to un-priced quality differences within ticket categories (Leslie and Sorensen, 2009). This is an interesting issue for future research.

5-Summary

This work is, to our knowledge, the first systematic study of the relationship between price discrimination and revenue at the level of an entire industry. We make two main contributions. First, we take a panel data approach to estimate the impact of price discrimination on revenue. Second, we test comparative static predictions implied by the theory on how market characteristics should influence the return to price discrimination.

We find that price discrimination increases revenue on average by 5 percent in our sample. Interestingly, our baseline estimates are of the same order as Leslie’s (2004) results, notwithstanding the fact that we use a fundamentally different empirical approach and a radically different data set, and that the two industries share few features other than that they produce entertainment. Another finding is that the return to price discrimination increases in markets where demand is more heterogeneous. Finally, we find decreasing returns to each additional seating category.

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[27] Surprisingly, the option of using three categories peaked in the mid-90s and was not very common toward the end of our sample.

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Figure 1. The frequency of price discrimination in the six cities with over 300 concerts during 1992-2005.

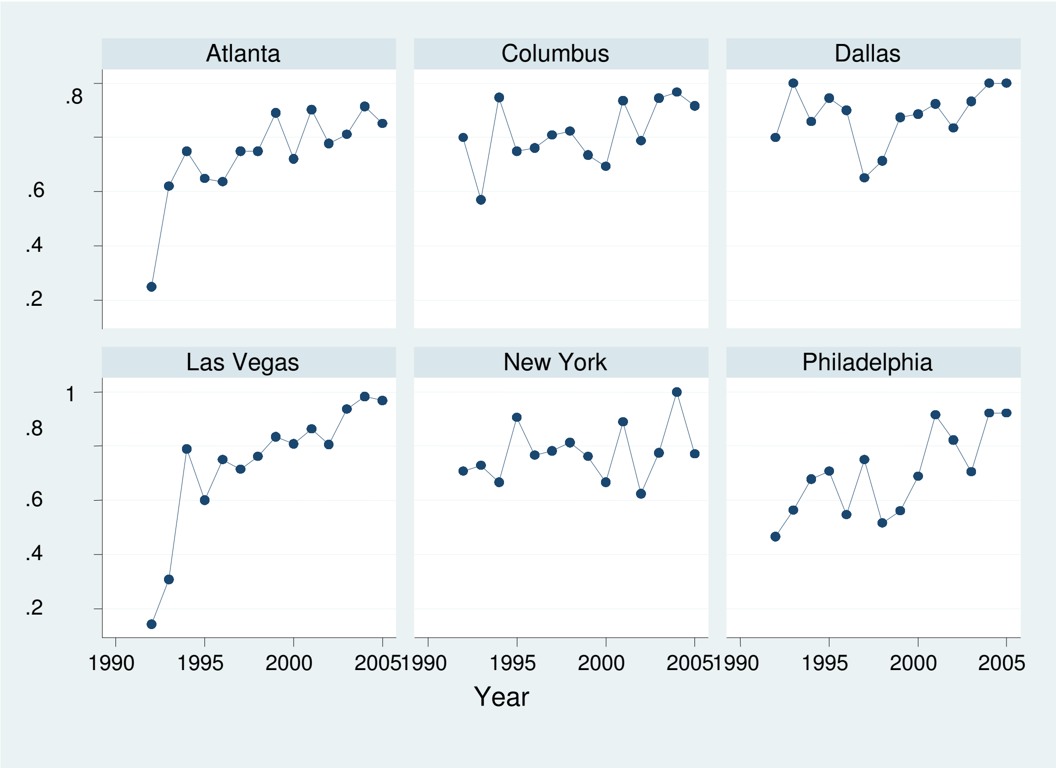

Figure 2. The frequency of price discrimination for the artists with over 300 concerts during 1992-2005.

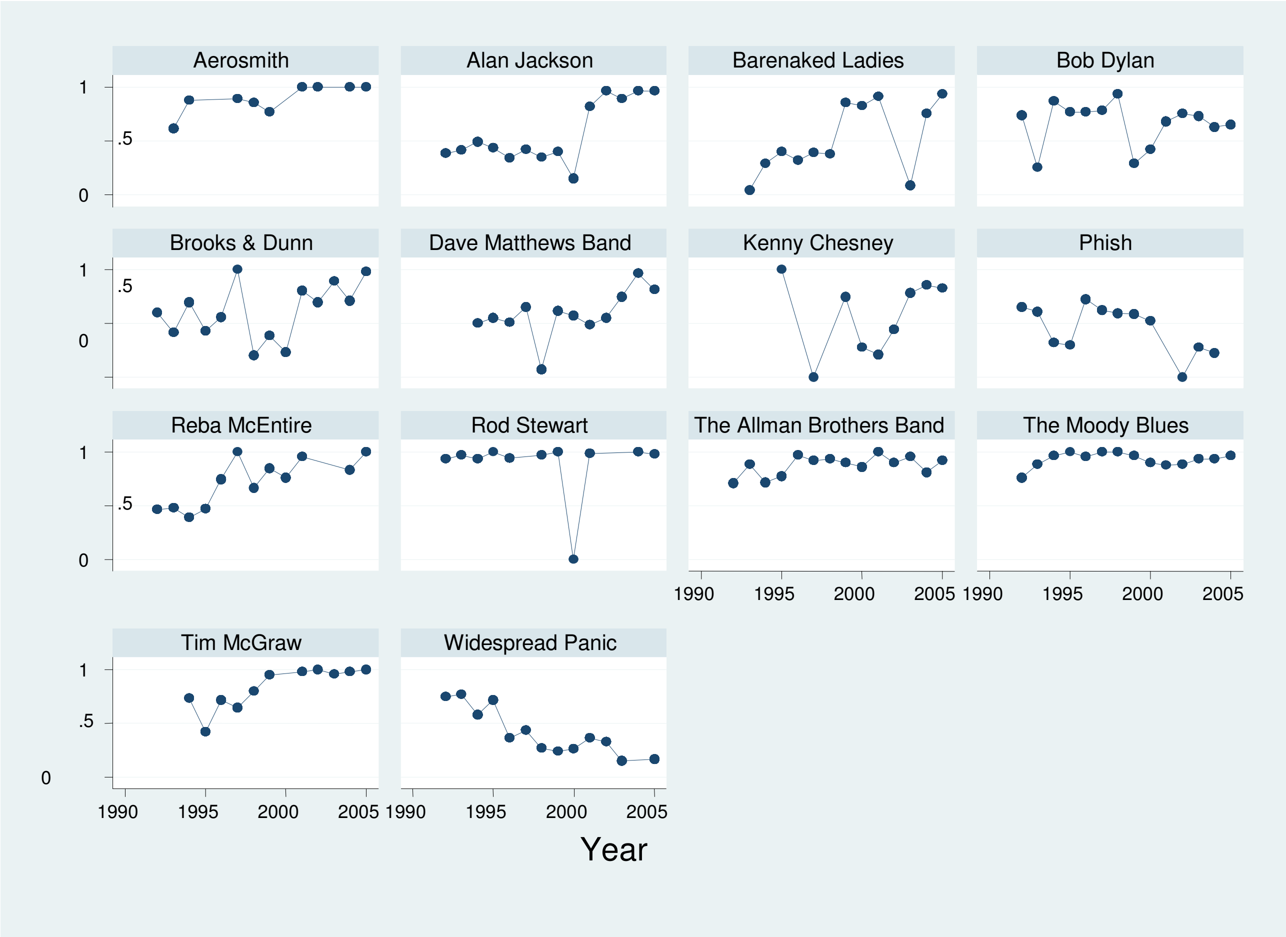

Table 1. Summary statistics (21,120 concerts).

Variable	mean	s.d.	p10	p25	p50	p75	p90
Capacity utilization	.85	.19	.54	.72	.94	1	1
Price discrimination	0.75	0.43	0	1	1	1	1
Attendance	13,005	13,965	3,271	6,162	10,016	14,939	22,736
Revenue ($)	544,033	842,277	93,084	167,929	317,270	620,075	1,097,739
Number of prices	1.99	0.77	1	2	2	2	3
Capacity	15,279	14,240	4,231	7,889	12,684	18,500	25,000
Average price	38.87	26.22	18.50	23.59	32.29	47.00	65.00
Highest price category	55.69	71.34	22	28	40	61	85.5

Table 2. The impact of price discrimination on concert revenue.

	(1) ln(revenue)	(2) ln(revenue)	(3) ln(revenue)	(4) ln(revenue)	(5) ln(revenue)
Price discrimination	0.58***	0.24***	0.052***	0.049***	0.053***
	(0.04)	(0.03)	(0.013)	(0.009)	(0.009)
ln(capacity)		1.04***	0.939***	0.806***	0.818***
		(0.02)	(0.020)	(0.019)	(0.019)
Artist f.e.?			Yes		
City f.e.?			Yes		
Year f.e.?			Yes	Yes	Yes
Tour f.e.?				Yes	Yes
Venue f.e.?				Yes	Yes
Promoter f.e.?					Yes

Note: The dependent variable is the log of gross concert revenues. Robust standard errors in parentheses clustered by city in columns 1-3, by venue in columns 4 and 5. The number of observations is 21,120. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. The impact of price discrimination on concert revenue (with interaction terms).

	(1) ln(revenue)	(2) ln(revenue)	(3) ln(revenue)	(4) ln(revenue)	(5) ln(revenue)
Price discrimination	0.040***	0.064***	0.050***	0.051***	0.048***
	(0.009)	(0.008)	(0.011)	(0.011)	(0.008)
ln(capacity)	0.734***	0.940***	0.698***	0.693***	0.906***
	(0.007)	(0.005)	(0.011)	(0.011)	(0.005)
Artist f.e.?	Yes	Yes	Yes	Yes	Yes
City f.e.?	Yes	Yes			Yes
Year f.e.?	Yes	Yes	Yes	Yes	Yes
Venue f.e.?			Yes	Yes	
Promoter f.e.?					Yes
Artist-year f.e.?	Yes		Yes	Yes	
Artist-city f.e.?	Yes				
Artist-venue f.e.?			Yes	Yes	
City-year f.e.?		Yes			
Artist-promoter f.e.?					Yes
City specific trend?				Yes	

Note: The dependent variable is the log of gross concert revenues. The number of observations is 21,120. Robust standard errors in parentheses clustered by city in columns 1, 2, and 5, by venue in columns 3 and 4. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. The determinants of the return to price discrimination.

	(1) ln(revenue)	(2) ln(revenue)	(3) ln(revenue)
PDxMedian household income (/1,000)	0.0029*	0.0023***	0.0021***
	(0.0015)	(0.001)	(0.001)
PDxCity Population (/1,000,000)	0.046***	0.021***	0.023***
	(0.012)	(0.005)	(0.005)
PDxLn(Gini ethnical heterogeneity index)	0.079***	0.055***	0.052***
	(0.023)	(0.014)	(0.014)
PDxLn(Gini occupational heterogeneity index)	0.454**	0.0039	-0.012
	(0.226)	(0.302)	(0.301)
PDxLn(Gini income heterogeneity index)	0.091	0.564	0.624
	(1.176)	(0.599)	(0.629)
Price Discrimination (γ_2)	0.131	0.060	0.063
	(0.153)	(0.128)	(0.130)
Ln (capacity)	0.933***	0.804***	0.815***
	(0.020)	(0.019)	(0.019)
Artist f.e.?	Yes		
City f.e.?	Yes		
Year f.e.?	Yes	Yes	Yes
Tour f.e.?		Yes	Yes
Venue f.e.?		Yes	Yes
Promoter f.e.?			Yes
The return to price discrimination : $\gamma_2 + Y^*\gamma_3$	0.046	0.053	0.057

Note: The dependent variable is the log of gross concert revenues. The estimated coefficients for the interaction between PD and the proxies for the heterogeneity in the population are the elements of the vector γ_3 in model (1). The estimated coefficient of PD is γ_2 in model (1). Robust standard errors are in parentheses, clustered by city in column 1, by venue in columns 2 and 3. The last row reports the estimated return to price discrimination, $\gamma_2 + Y^*\gamma_3$, where Y* includes the mean values of the variables in Y. The number of observations is 20,815. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. The return to the number of pricing categories.

	(1)	(2)	(3)
	ln(revenue)	ln(revenue)	ln(revenue)
Two price categories	0.046***	0.047***	0.034***
	(0.013)	(0.009)	(0.009)
Three price categories	0.077***	0.067***	0.069***
	(0.018)	(0.012)	(0.012)
Four price categories	0.098***	0.080***	0.070***
	(0.028)	(0.016)	(0.016)
ln(capacity)	0.938***	0.806***	0.733***
	(0.020)	(0.019)	(0.007)
Artist f.e.?	Yes		Yes
City f.e.?	Yes		Yes
Year f.e.?	Yes	Yes	Yes
Tour f.e.?		Yes	
Venue f.e.?		Yes	
Artist-year f.e.?			Yes
Artist-city f.e.?			Yes

Note: The dependent variable is the log of gross concert revenues. Robust standard errors are in parentheses. The number of observations is 21,120. * significant at 10%; ** significant at 5%; *** significant at 1%