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

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Abstract: Concert tickets can either be sold at a single price or at multiple prices corresponding to different seating categories. We study the relationship between price discrimination and revenue by examining variations in the number of seating categories across concert, tour, artist, location, and time. Offering multiple seating categories leads to revenues that are approximately 5 percent higher than with single price ticketing. The return to price discrimination is higher in markets with more heterogeneous demand, in smaller venues and in more competitive markets. The return of increasing from three to four categories of seating is about half that of increasing 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, based on analysis of a rich panel dataset of pop music concerts covering a large share of the US concert industry over multiple years.

We make two contributions. First, we estimate the impact of price discrimination on revenue. Second, we document how this impact depends on product, seller, and market characteristics, factors that have been shown to matter in the theoretical literature (Stole, 2007, and Rosen and Rosenfield, 1997). For example, we show that the return to price discrimination is higher in markets that are more heterogeneous in term of occupational diversity, income inequality, or ethnical heterogeneity.

Concerts for popular music offer a unique environment for the study of price discrimination, first of all because concert pricing provides a textbook application. The practice of selling tickets for different seats at the same venue at widely disparate prices can be unambiguously attributed to price discrimination: the seating capacity and the distribution of seat quality are givens, and the only issue is whether to sell different seats at the same or at different prices. In contrast, most studies in the literature present cases where price differences among products may be the result of variations in marginal cost, rather than of price discrimination (Shepard (1991), Clerides (2004)). Another advantage of studying the concert industry is that its pricing policies are relatively straightforward.

For each venue, a pricing policy divides the venue into categories, and establishes a price for each.

Our dataset covers over 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 on 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 on revenue. We can thus investigate how the former influences the latter. Finally, we also collected information on the characteristics of the product (venue, genre of music, type of tour), of the vendor (information about the artist and band), and of demand (features of the local population).

A concert may offer all seats at the same price (single-price ticketing), or split seats in two or more seating categories, each with its own price. In the core of this work, we say that a concert uses price discrimination if there are two or more seating categories. We compute the effect of using price discrimination on revenue. After controlling for artist, city, and year fixed effects, we find that price discrimination is associated to about 5 percent greater revenues. This preliminary finding is open to diverse interpretations. Above all, our estimate may reflect both a selection effect and the causal effect of price discrimination on revenue. Our baseline results, however, do control for market fixed effects (city dummies), product fixed effect (artist), and year fixed effects. Still, other sources of unobserved heterogeneity may be correlated with the decision to price discriminate, thus confounding the interpretation of the baseline finding.

We pursue three empirical strategies to investigate whether the relationship we identify is causal. First, we follow the same approach as Nevo and Wolfram (2002) and control for unobserved heterogeneity by exploiting the rich nature of our panel. The robustness of the baseline results with a restricted set of fixed effects, to a wide set of richer specifications with interacted fixed effects and additional control variables, suggests that taking a difference in difference in difference (product, location, time) is sufficient to control for unobserved heterogeneity.

Second, we pursue an instrumental variable approach that combines the insight of Nevo and Wolfram (2002), who propose exploiting the regional average propensity to use price discrimination, with the information that we have on the identity of each concert's promoter. The instrumental variable we use is the promoter-city-year propensity to price discriminate, measured as a city-year average (excluding the concert being instrumented). Promoters have expertise that vary from city to city and year to year due to manager turnover, learning, and change in local environment. Since artists typically use the same promoter for different cities in the same tour, this variation across cities in the promoter's experience is correlated with the use of price discrimination, but not with remaining unobserved heterogeneity. Our estimates do not change when we instrument price discrimination.

Another approach to establishing causality is to examine the theoretical mechanism through which price discrimination might influence revenue. This provides a completely new way of looking at the evidence. We no longer attempt to measure the average impact of price discrimination on revenue, as in the previous two approaches. Rather, we study how this relation depends on demand and product characteristics. Building upon Rosen and Rosenfield's (1997) model of ticket pricing, we demonstrate that the return to price discrimination should decrease with venue size but increase with the income of the local population and with a less homogeneous population of consumers. These specific predictions made by the theory can be tested. This approach has two advantages. First, it

[3] If we increased the sample to include the top 500 grossing artists over the same

allows us to seek evidence of a specific causal mechanism of price discrimination on revenues. Second, as we only use variability in revenues across concerts that do use price discrimination, we can disregard issues related to the possibility that the decision to price discriminate is correlated with unobserved characteristics.

As predicted, we find that the return to price discrimination is higher in markets where the local public is more heterogeneous and this holds when we consider heterogeneity in age, occupation, or ethnicity. We also find that the return to price discrimination increases with income and decreases with venue capacity. The consistency of this third set of results with standard economic theory further corroborates our interpretation of the initial results. These results diverge from those of previous empirical studies, which have rejected the theoretical predictions of monopoly models of price discrimination (Verboven (1999) and Nevo and Wolfram (2002)).[4]

After establishing these results, we investigate two issues of interest for policy-makers and industrial economists. First, we consider the role of competition, measured by the average frequency of concerts offered each year in a given city. We find that competition does not influence the level of revenue but increases the return to price discrimination. This result is inconsistent with models of price discrimination and competition (e.g., see Stole (2007) for a review), but it could also be explained by the greater amount of information available on how to segment a venue in more competitive markets. Our findings also complement the empirical work of Verboven (1996) and Busse and Rysman (2005). Both studies show that the extent of price discrimination increases with market competition. In contrast, we consider the interacted impact of price discrimination and competition on revenue.

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period, for example, the top 100 artists would represent 70 percent of total revenue.

[4] A candidate explanation is that these past studies considered oligopolistic industries, whereas our application more closely matches the standard case of monopoly pricing.

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

The rest of this paper is organized as follows. We briefly summarize the relevant literature. We then offer some brief information about the concert industry and present the data, outlining why and how sellers split venues into different seating sections. Section 3 introduces the econometric framework and discusses the issue of causality in the interpretation of the relationship between price discrimination and revenue. Section 4 presents the results, and Section 5 concludes.

Literature

Our evidence contributes to previous non-structural studies of price discrimination (Shepard (1991), Nevo and Wolfram (2002), Busse and Rysman (2005)). As mentioned earlier, one issue that has received much attention is whether the practice of selling similar goods at different prices (price differentiation) is due to price discrimination or to marginal cost pricing. In contrast, this paper selects an industry where price differentiation is unambiguously due to price discrimination and then investigates the relationship between price discrimination and revenue.

This study complements the evidence from structural micro econometrics (Leslie 2004, Miravete and Röller 2004, McManus, 2008). In contrast with most structural studies, however, our evidence is based on an entire industry. It is most closely related to 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 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 using variability across a large number of markets.

Our work also contributes to the empirical literature of cultural economics (Krueger (2005) and Huntington (1993)) and to the theoretical literature on ticket pricing (Rosen and Rosenfield (1997) and Courty (2003)).

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

The modern touring industry was born in the late 1960s when a few bands such as the Rolling Stones and Led Zeppelin regularly started to tour a variety of arenas and stadiums, using their own experienced crew to take care of the sound, staging and lighting. In the 1980s, advances in technology allowed bands to offer even more ambitious stage shows that were louder and brighter, and available to ever-larger 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) were given as 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. The agent then looks for promoters to organize the event in each city. The artist

[5] The information on the touring industry presented in this section was collected by interviewing concert promoters as well as two professors who teach courses on

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, and this 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 some also add local promoters in some cities to tap into the local expertise so crucial for success. On average, the largest promoter within a tour organizes 46 percent of the concerts, while the largest two organize 59 percent. In 25 percent of the tours, the largest two promoters are involved in pricing more than 92 percent of the concerts. A few artists do everything in-house and directly contact the venues. 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 similar stage, and are marketed together.

Pricing and promoter knowledge

Each event is unique and there is no set formula for pricing a concert. Ticket prices are typically determined when the tour is announced and remain unchanged.[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.

Promoter experience with price discrimination varies across local markets. We elaborate on this point because it plays a key role in motivating our choice of instrumental

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concert promotion. Some of the information was also drawn from recent books and industry manuals on concert promotion, in particular Waddell et al. (2007).

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

variable. Waddell et al. (2007) reports that "the art of concert promotion is derived from the experience, instinct, knowledge of the event to promote and who it appeals to, innate sense of timing, and flair necessary to capture public awareness" (p. 193) and comment in detail on the role of local information: "we work with each promoter and try to tap into their vast knowledge of their local market to make the right call on when to put a show on-sale, ticket scaling options and when you roll into multiple shows" (p. 47). The first quote implies that pricing solutions may be idiosyncratic and promoter specific, while the second refers specifically to the number of seating categories (scaling) and emphasizes the role of the promoter's market-specific knowledge. Pricing policies are event and promoter specific, which implies that some of the policy variations in our sample may be a result of promoter knowledge, market-specific know-how, and even idiosyncratic individual style.[7]

2-1 Data

This study focuses on the primary market for concert tickets, with data from two sets of sources. The core of the data was collected by Billboard 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 capacity available, 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 information regarding the bands from music websites, artist websites, and the Rolling Stone Encyclopedia of Rock and Roll.

[7] In fact, Waddell et al. (2007, p. 199) even 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, and if it works in one place it might work in another. The agent giving you that kind of information is terrific."

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 the local demand and can be aggregated at the level of city or state.[8] 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, what type of tour. 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 for different seats are offered at multiple prices. This definition of price discrimination distinguishes between unsophisticated pricing (general admission) and sophisticated pricing (differentiated seating). While the core of this paper focuses on this broad distinction, Section 4.6 computes the return to each additional pricing category. Beyond these distinctions, we do not attempt to measure the intensity of price discrimination (Clerides, 2004).[9]

[8] 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.

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

Figure 1, 2, and 3 plot the fraction of concerts that use price discrimination for the cities, artists, and promoters with the largest number of concerts in our sample. These plots point out important sources of heterogeneity. Price discrimination varies greatly across cities, artists, and promoters. There is a general trend toward greater use of price discrimination (Connolly and Krueger, 2006).[10] But there are also many variations on this trend, as well as notable exceptions.[11]

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.[12] This figure is consistent with the hypothesis that the choice to price discriminate depends on product and demand characteristics, but it also indicates that about half of the variations in the use of price discrimination cannot be explained by these fixed effects. 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,

[10] 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 (young artists are over-represented late in the sample and all artists get older throughout the sample) and the fact that the artist life cycle influences the use of price discrimination (Courty and Pagliero, 2008).

[11] 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.

[12] 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, and promoters organizing concerts in the same year, city and city-year combinations.[13]

We conclude that there are variations in the use of price discrimination even after we control for time, artist, city or promoter fixed effects, or when we focus on variations within sub-cells of artist-year, artist-city, artist-promoter, or city-year. Unexplained variability in price discrimination may be due to variability in artists' willingness to experiment with new pricing policies or attitudes toward price discrimination, heterogeneity in promoter experience, access to updated local market information, as well as to turnover within promotion firms or implementation constraints preventing the use of price discrimination. The next section explains how different sources of variation are used to estimate the impact of price discrimination on revenue.

3-Empirical Framework and Interpretation

Our empirical objective is to estimate the impact of price discrimination on revenue. This estimation problem falls within treatment effect literature once one labels the concerts that use price discrimination as the treated ones (Wooldridge, 2002, Chapter 18). One would ideally want to randomly manipulate treatment and then measure the impact of doing so on revenue. In the absence of such ideal conditions, one may leverage the fact that the use of price discrimination varies for exogenous reasons. We estimate variants of the following general model,

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

[13] Of the 2,190 pairs of artist and promoters that organized at least two concerts in the sample, only 62 percent either always used price discrimination or never used it at all. 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.

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, such as venue capacity and number of artists performing, affecting revenues for concert i; 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 (a full list of the variables included in X_i and Y_i is presented in Table 7). $\Phi^1{}_i$ is a vector of indicator variables that could include artist or tour, city or venue, promoter, and year dummies and also interactions between them; γ_0 and γ_2 are scalars, γ_1, γ_3 and γ_4 are vectors of parameters, and ε_i is an error term that could capture, for example, demand shocks that are realized after prices are set. We can estimate the return to price discrimination under the assumption that $E(\varepsilon|X,Y,PD,\Phi^1)=0$. If this is the case, the OLS estimate of γ_2 is the average treatment effect (the average return to price discrimination) if there are no variables in Y. Otherwise, the average treatment effect is $\gamma_2 + Y^*{}_i\gamma_3$, where Y* includes the sample mean of the variables in Y, and the vector γ_3 is the marginal return of the variables in Y.

Selection to treatment

To determine whether the assumption $E(\varepsilon|X,Y,PD,\Phi^1)=0$ holds, one needs to understand what determines treatment. Artist and promoter use price discrimination if doing so increases profits. We focus on a simple treatment rule that illustrates the sources of identification that can be exploited with our data,

$$PD = \begin{cases} 1 & \text{if} \quad I(X,Y,\Phi^2)[R(PD=1,X,Y,\ \Phi^1) - C(X,Y,\Phi^2)] > R(PD=0,X,Y,\Phi^1) \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

R(PD=x,.) is the revenue if $PD=x \in \{0,1\}$. Φ^2 is a matrix of dummy variables that could be different from Φ^1. I is an indicator variable that is equals to one if the promoter knows how to implement price discrimination (how to split the venue and set prices). We introduce I because promoter experience is key to the success of price discrimination. The artist can earn the price discrimination revenue R(PD=1) only if I=1. C is the cost of implementing price discrimination and it depends on the match between the stage used in a given tour and the venue where the concert takes place. C may also capture other cost shifters such as variations in distribution channels, and local regulatory constraints that differentially apply to different types of music.

Selection on Observable Variables

For the sake of exposition, we ignore for now the interaction variables ($Y=\emptyset$). The condition $E(\varepsilon|X,PD,\Phi^1)=0$ can be defended on several grounds. It holds if some dummy variables enter the selection equation in Φ^2 (generating variations in PD) but not the revenue equation in Φ^1 (so that there exist some exogenous variability in PD). Two sets of interacted fixed effects may satisfy these conditions. Consider first variations in C due to venue-tour interactions. The artist commits to a stage design for an entire tour (this includes overall stage setting, lights, special effects, number of players in the band). The artist faces a different cost of implementing price discrimination in each venue that depends on the match between the stage design and venue characteristics, distribution of seats, and security constraints. On the other hand, there is no reason for why the venue-tour interaction should belong to Φ^1.

A similar argument can be made that promoter-city fixed effects enter (2) through I but not (1). There is typically one main promoter for each tour. This promoter, however, has local experience that varies from city to city (the promoter-city dummies belongs to Φ^2). But artists choose promoters on the basis of how well they match the entire tour, that is, on their ability to raise the average level of revenue across all cities. Thus, the promoter-city dummy does not belong to Φ^1 under the assumption that local experience influences revenue only through the price discrimination decision.

For the assumption $E(\varepsilon|X,PD,\Phi^1)=0$ to be violated, it must be the case that the decision to price discriminate is correlated with some unobserved variable that affects concert revenue. But $\Phi^1\gamma_4$ can account for a large set of fixed effects and interacted fixed effects that allow for many sources of unobserved heterogeneity and very general selection rules. Tour fixed effects allows for different tours attracting different publics. It also controls for artist fixed effects because the vast majority of tours in our sample include a single artist. Venue fixed effects controls for venue heterogeneity (physical constraints, location). In addition, we can include interacted fixed effects that control for the possibilities that different artists face different fan populations in different cities, that their typical fan varies from year to year, that the fan population in a given city varies over time, and that some promoters may have a different impact on revenue depending on the artist.

$E(\varepsilon|X,PD,\Phi^1)=0$ could be violated if the return to price discrimination varies across concerts and the artist chooses to price discriminate when the return to price discrimination is high. In this case, however, the estimate of the average treatment effect in model (1) only needs to be reinterpreted as the average treatment effect on the treated (Heckman and Robb, 1985).[14] To our knowledge, there is no other compelling economic argument for why $E(\varepsilon|X,PD,\Phi^1)=0$ should be violated. There still remains the possibility that, for reasons that are not economic, selection takes place on unobservable variables that are

[14] 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 $\gamma'_2=\gamma_2+E(\alpha_i|PD=1)$, while the IV estimate gives the average treatment effect γ_2 (Heckman and Robb, 1985). In our application, the two estimates give similar values suggesting that the random component α is not important.

correlated with the random component of revenue. An instrumental variable approach takes care of this possibility.

Instrumental Variable

Equation (2) suggests using as an instrument a variable correlated with I or C but not with ε. While variations in C are purely idiosyncratic (concert specific), I varies at the city level for each promoter. We propose to use as a proxy for I the promoter's propensity to use price discrimination for all the other concerts that took place in the same city and year as concert i. Formally, let $P^j_i=1$ if concert $j \neq i$ takes place in the same city and year as concert i and has the same promoter as concert i and $P^j_i=0$ otherwise. We use as instrument the variable Z, defined as

$$Z_i=E(PD_j | P^j_i=1).$$

The economic rationale for this IV is based on the argument made earlier that identification can be obtained from variations in I. Such variations in I are exogenous if promoters are chosen to match an entire tour but their local price discrimination experience varies from city to city and year to year due to differences in management style, or staff turnover at the city level.[15] Formally, this is a valid instrument under three conditions. First, Z is correlated with PD which is the case because all concerts organized by a given promoter in the same city-year share the same local experience Z. If local experience matters, we would expect that $dPD/dZ>0$, a condition that can be tested in the first stage regression. Second, Z is excluded from the structural model determining revenues (1). This is true if, holding promoter identity constant, local price discrimination experience influences concert revenue only through the use of price discrimination. Third, $E(\varepsilon|X,\Phi^1,Z)=0$, and a

[15] We also consider the same IV but at the promoter-city level, and the results are robust. Our IV approach is similar to Nevo and Wolfram (2002) but richer since we also use information on promoter identity.

sufficient condition for this to be the case is that the concert-specific shocks ε_i are independent across concerts within a given city and year.

According to the selection equation, we could in theory have used as instruments a set of dummies for each promoter-city interaction. The exclusion condition for Z is weaker than that for this alternative set of IVs. Although it is plausible that the promoter-city dummies could enter the revenue equation even after having controlled for promoter and city fixed effects, local price discrimination experience is much more finely defined and it is not unreasonable to assume that is not correlated with other skills (of the local promoter) that also influence revenues.

Interaction Effects

If the unobserved demand and supply characteristics affecting revenues through the error term are uncorrelated with our control variables, $E(\varepsilon | \Phi^1,PD,X,Y)=0$, then the average treatment effect is $[\gamma_2 + Y^*_i\gamma_3]$. Even if the above condition does not hold, we can still obtain an unbiased estimate of the vector γ_3, which measures the impact of variables in Y on the return to price discrimination, as long as $E(\varepsilon | \Phi^1,PD=1,X,Y)=0$. Studying the sign and magnitude of the coefficients in γ_3 is interesting per se, because one can test theoretical predictions on how the variables Y_i should influence the return to price discrimination (for the treated group). Doing so, we use only variability in revenues across concerts that do use price discrimination. The validity of this approach rests on the economic foundations of the mechanisms that justifies that the return to price discrimination should depend on the variables in Y.

According to monopoly theory, the gain to price discrimination depends on the distribution of consumer preferences and the marginal cost function. Matters are simpler in our case study, because marginal costs are zero, and even more importantly, physical constraints dictate the quantity of seats that can be allocated to each category. Rosen and Rosenfield (1997) propose a simple model of ticket pricing and derive general predictions on how the return to price discrimination depends on market primitives. They assume that the venue can be split into n_s seats of quality s, s=l,h. 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 $v^{H}_{h} - v^{H}_{l} > v^{L}_{h} - v^{L}_{l}$. There are not enough high types to fill the entire venue but there are enough high types to fill the high quality seats (this is a reasonable assumption in the concert industry). Under price discrimination, the monopolist fully extracts the surplus of the low type consumers, binds the incentive compatibility constraint of the high types, and earns revenue

$$R(PD=1)=n_l v^L_l + n_h(v^L_l + (v^H_h - v^H_l))$$

which can be rewritten as

$$R(PD=1)=[n_l+n_h]v^L_l + n_h(v^H_h - v^H_l).$$

Since the first term above corresponds to the revenue under uniform pricing $R(PD=0)=[n_l+n_h]v^L_l$, the percentage increase in revenue from price discrimination,

$$[R(PD=1)-R(PD=0)]/R(PD=0)=[n_h/(n_l+n_h)][(v^H_h - v^H_l)/v^L_l] \quad (3)$$

depends on the fraction of high quality seats and on the variability in preferences in the population. We set out to test whether demand and supply characteristics that influence these two terms have the predicted sign on the estimated return to price discrimination.

4-Results

The results are presented as follows. Table 2 restricts $\gamma_3=0$ and includes no interacted fixed effects. The aim is to estimate the average (across the top 100 artists) impact of price discrimination on revenue. Table 3 reports the results including interacted fixed effects for artist-year, artist-city, city-year and artist-promoter. This demonstrates the stability of our initial results after controlling for a wide variety of unobserved heterogeneity. Tables 4-6 present the IV regression results. Table 7 reports the estimates of interaction effects γ_3.

4-1 Impact of Price Discrimination on Revenue

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 columns 3 adds artist, city and year fixed effects. Controlling for capacity reduces the impact of price discrimination by half. The reason 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.[16]

We compare the results of the fixed effect estimator in column 3 with the corresponding random effect estimator (Hausman test). Since we reject the null of no change in the parameters of the remaining control variables, we can deduce that the fixed effects capture relevant unobserved heterogeneity. In fact, the return to price discrimination is significantly higher (24 percent) when we do not include any fixed effects than when we do (5 percent).

In column 4, we replace the artist fixed effects with tour fixed effects and the city fixed effects with venue fixed effects. This is a richer specification, since, on average, each artist is observed in more than 6 tours in the sample (and very few tours have multiple artists).

[16] When we add only year fixed effects in addition to capacity, the impact is 9 percent (not reported). This sharp decrease could be explained by the simultaneous increase in revenue and use of price discrimination during our sample period as documented by Krueger (2005) but this figure over-estimates the role of time because age

The tour fixed effects capture common features of the event (e.g., stage and songs). Venue fixed effects not only control for the city-specific demographics but also for venue-specific characteristics, such as location, type (theater or stadium) and overall experience. In column 5, we further add a series of promoter fixed effects, capturing the time invariant characteristics of the main promoter for each concert. This is important because the promoter can influence the pricing and marketing of a concert.[17] The impact of price discrimination is positive and significantly different from zero at conventional levels. The magnitude is also economically significant: revenues are 5 percent higher 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 accounts for over $50 million for the top 100 artists.

Interestingly, the coefficient estimates in Table 2 are stable across the last 3 columns, suggesting that the finer controls in column 4 and 5 do not reveal further sources of unobserved heterogeneity relative to the simple model with artists, city and year fixed effects in column 3.[18] In the next section, we show that this is also the case when we allow for more general sources of unobserved heterogeneity.

4-2 Controlling for Interacted Fixed Effects

increases over the sample period and older artists earn more and are more likely to price discriminate.

[17] The results are robust when we also add log-capacity squared to capture further non-linear capacity effects.

[18] We also tested for the existence of unobserved heterogeneity for some of the additional fixed effects included in Table 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 unobserved heterogeneity,,but such unobserved heterogeneity does not affect the economic magnitude of the estimate of the return to price discrimination. Because unobserved heterogeneity could matter, we consider specifications with interacted fixed effects in the next subsection and we also include a large subset of fixed effects in Section 4-4.

We leverage the feature of our dataset that the use of price discrimination varies within sub-cells of artist-year, artist-city, artist-promoter, or city-year (see discussion in Section 2.2 and Figures 1-3). Although, in principle, one could simultaneously introduce all the interaction terms in model (1), in practice, the flexibility of the specification comes at the cost of a reduction in degrees of freedom, so we report the results using different combinations of fixed effects. In Table 3, column 1, we introduce the interaction between artist and city. This captures differences in preferences for bands across cities. We also introduce the interaction of artist and year fixed effects to capture the possibility that the demand for a given artist changes over time, due to aging of the population or changes in the artist's public. In column 2, we include the interaction of city and year fixed effects, to account for the change in the number and preferences of fans within a city, as well as other time-varying city-specific characteristics. In column 3, we include, in addition to artist-year fixed effects, 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. In column 4, we further add city specific linear trends to capture the within-city change in preferences and demographic variables.[19] Finally, 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. In spite of the wide variety of heterogeneity that is accounted for, the impact of price discrimination is systematically positive and statistically significant at conventional levels. Price discrimination is associated with an increase in revenues between 4 and 6 percent.

An important concern is that the adoption of price discrimination over time may be correlated with changes in demand characteristics. For example, demand changes may increase the profitability of price discrimination. But all our specifications control for year

[19] At this point, adding city-year fixed effects reduces the degree of freedom too

fixed-effects. In addition, column 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. Further, column 2 controls for city-year fixed effects, ruling out city heterogeneity in change in demand. To conclude, endogenous adoption of price discrimination correlated with time is unlikely to be driving our results.

4-3 Instrumental Variable Regression

Tables 4-6 report the results of the IV specifications. Our instrument Z varies significantly both across promoters and for the same promoter (summary statistics are provided in Table 4). The first stage results are reported in Table 6. In the first stage, our IVs are always significantly correlated with the use of price discrimination at a 1 percent confidence level, and we reject the null of weak IV (Stock and Yogo 2001). [20,21]

The IV estimates in Table 5 vary between 6.8 and 9 percent. Overall, the magnitude of the impact of price discrimination is in line with previous results, although the standard errors significantly increase. In column 3, we use as IV the frequency of price discrimination for concerts organized by the same promoter in the same city, but for all years in the sample. The results are not significantly affected.

4-4 The Determinants of Price Discrimination

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much.

[20] Table 6 reports the F-test of the significance of the excluded instrument in the first stage. The critical value for the Weak-IV test based on the first stage F-statistic is 8.96. The null is that the instrument is weak, in the sense that the nominal 5 percent 2SLS t-test of the hypothesis that price discrimination does not affect revenue has size potentially exceeding 15 percent (Stock and Yogo 2005).

[21] The weak-IV test fails when we use the specification in column 3 and add promoter fixed effects (results are not reported). The second stage coefficient for price discrimination, however, is still positive (and larger than in the other columns).

In Table 7, column 1 we report the estimated coefficients for γ_3. Overall, the average treatment effect, $[\gamma_2 + Y^*_i\gamma_3]$ where Y* includes the sample mean of the variables in Y, is not significantly different from the estimates in the previous sections. Our benchmark model is Table 2, column 3 (which includes artist, city and year fixed effects). Equation (3) says that the return to price discrimination increases with $[n_h/(n_l+n_h)][(v^H{}_h-v^H{}_l)/v^L{}_l]$. We investigate how observable characteristics are likely to influence this expression.[22]

Demand and Product Characteristics

We select variables for which we can make a case to sign their interacted impact with price discrimination (impact on ln(R(PD=1))-ln(R(PD=0))) based on equation (3). For the sake of brevity, we present only informal arguments, keeping in mind that formal comparative statics could be derived.

Population heterogeneity: We hypothesize that the ratio $(v^H{}_h-v^H{}_l)/v^L{}_l$ is higher in more heterogeneous markets. Under that hypothesis, the return to price discrimination increases with market heterogeneity. We consider three different measures of market heterogeneity which are computed using the Gini diversity index at city or place level using data from the 2000 census.[23] *(a) Occupational diversity*: We compute the Gini diversity index using data on the proportion of the population in different occupational groups, as reported by the census (management, services, sales, farming, construction, production). A one percent increase in the diversity index implies a 0.5 percent increase in the return to price discrimination. *(b) Income diversity.* The return to price discrimination is higher in cities in which income heterogeneity is higher, measured by the Gini diversity index using 16

[22] We also include dummy variables for 11 months (February to December) in X and Y to control for possible seasonality in revenues and in the return to price discrimination. The inclusion of these further controls does not affect the results .

income brackets. Although the standard error is large and the coefficient is not significantly different from zero. *(c) Ethnical heterogeneity.* Ethnical heterogeneity is measured by the Gini diversity index using three racial groups (white, black, other). The return to price discrimination is higher in cities with a more ethnically diverse population. This is consistent with diversity in preferences for quality being correlated with ethnic group heterogeneity. A one percent increase in the heterogeneity index implies a 0.06 percent increase in the return to price discrimination.

Income level: The level of average household income (by city or place) has a positive and statistically significant impact on the return to price discrimination. An increase in average household income of $10,000 implies a 3 percent increase in the return to price discrimination. This is consistent with equation (3) under the assumption that the income elasticity of the demand for a concert is higher for richer people (implying that the numerator in $(v^H_h-v^H_l)/v^L_l$ increases faster than the denominator).

Population Density (population per square mile, by city): The return to price discrimination is higher for concerts that take place in more densely populated areas.[24] One interpretation is that the diversity of public preferences is likely to increase with population density. In fact, larger and denser cities offer a larger and more differentiated set of consumer amenities (Glaeser et al., 2001).

Venue Capacity: The proportion of high quality seats, $n_h/(n_l+n_h)$, decreases with the size of the venue because high quality seats are located nearest to the stage, in what is known as the golden circle. Beyond a given distance, all seats are close substitutes. Once venue capacity reaches a certain level, a further increase in capacity mainly reflects an increase in the number of low quality seats, and the return to price discrimination should decrease with

[23] 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*.

the size of the venue.[25] The direct impact of venue capacity on revenues is positive. A one percent increase in the number of available tickets implies a 0.97 percent increase in revenue. This is consistent with the results in the previous tables. In addition, however, capacity has a negative impact on the return to price discrimination as predicted by the theory.[26] A one percent increase in capacity implies a 6 percent decrease in the return to price discrimination.

After consideration of the marginal effect of capacity alone, we now turn to the cross marginal effect between capacity and scaling (number of categories). The return to additional seating categories (moving from 2 to 3 and 3 to 4) should increase with capacity. Stated differently, the larger the venue capacity the greater the return of adding a category. To test the hypothesis, we interact log(capacity) with a dummy variable for having 2, 3 or 4 categories. We hypothesize that the interaction coefficient should increase with the number of categories. The results (not reported) are consistent with this hypothesis, and the difference between 2 and 4 categories is significant at 6 percent level. [27]

Column 2 in Table 7 presents the result of a specification with a large number of additional interaction variables and demonstrates that the results discussed earlier are robust. We comment here only on the impact of competition which is of special interest to

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[24] The size of the city has no significant impact on the return to price discrimination.
[25] This reasoning assumes that $(v^H_h - v^H_l)/v^L_l$ is independent of the size of the venue.
[26] In these regressions, capacity is the total number of tickets available in a given event. This variable could be greater than the venue size, because artists in 12 percent of the events offer multiple shows in the same city. We get similar results when we focus on the subsample of events with a single show. Similarly, when we split our capacity variable into one variable for venue size and another for number of shows (capacity is the product of these two variables), we get similar results for venue size as we did for capacity, and this is consistent with the theory (the coefficient estimate for number of shows is zero).
[27]The joint test that the difference between the coefficients for 2-3 and 3-4 categories are different from zero is significant at 10 percent level.

economists.[28] The relationship between price discrimination and competition has received much attention in the theoretical literature, but there is relatively little empirical evidence available (Busse and Rysman, 2005). Our contribution is to estimate how the return to price discrimination depends on competition.

We measure competition by the number of concerts taking place in a given market in a given year. Our measure of competition could be correlated with unobserved city characteristics, but we can control for such heterogeneity by including city fixed effects. Concert revenues are not significantly different on average in cities in which a larger number of concerts take place during the same year, regardless of whether price discrimination is used or not. The results do not change if we measure competition by musical genre. The same variable has a positive impact on the return to price

[28] Equation (3) does not permit to sign the impact of all the variables in column 2 on the return to price discrimination. Nevertheless, some interesting stylized facts may fuel future research. *Age*: The impact of age has an inverse U-shape with a peak in the late 30's. *Band prominence*: The impact of band prominence (measured by the number of words written in the biography of an artist on billboard.com) on price discrimination is positive and significant. *Male ratio*: The fraction of male members of the band has a negative impact on the return to price discrimination. One conjecture as to why is that male bands have more homogeneous audiences, which would imply more homogenous preferences over quality. *Other product characteristics*: the origin of the band (US or foreign), the genre (classified in three groups: rock, country and other) and the number of distinct artists featured, have no impact on the return to price discrimination. Interestingly, the number of artists featured has a direct positive impact on the level of revenues (independently of whether price discrimination is used): each additional band implies 3 percent higher revenues. Increasing the number of artists increases the level of demand but does not increase the return to price discrimination. *Number of concert in current year*: An increase of 10 concerts per year implies a 3 percent increase in the return to price discrimination. *Price differential:* a $100 increase in the price differential between the highest and the lowest category implies a 7 percent increase in the return to price discrimination. *Number of promoters*: there is a positive impact of the number of promoters on concert revenues. The number of promoters, however, is not associated with significantly higher returns to price discrimination. *Seasonality and time trend*: there is a significant increase in the overall level of revenues in November and December, but there is only weak within-year seasonality in the returns to price discrimination, with November and December having slightly higher returns. There is no evidence of any yearly trend in the return to price discrimination. This suggests

discrimination. On average, 10 more concerts implies a 2.6 percent increase in the return to price discrimination.

The first result is difficult to reconcile with some models of price discrimination and competition (e.g., see Stole (2007) for a review) but is consistent with the possibility that concerts may be poor substitutes. An interpretation for the second result is that when more concerts are being performed in a given city, more information may become available on how to optimally segment a venue, thus increasing the return to price discrimination.

4-3 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 adding complexity beyond two or three tariff options has only a small impact on revenue, 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

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that the adoption of price discrimination was not due to a change in consumer additional seating categories should be decreasing and small once a couple of categories are already offered.

In Table 8, 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 8, Column 1 and 2 include the same control variables as in Table 2, column 3 and 4. Table 8, 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 the 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 stronger 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?[29] 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, 2008). This is an interesting issue for future research.

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preferences.

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

5-Summary

This work is, to our knowledge, the first systematic non-structural study of the relationship between price discrimination and revenue at the level of an entire industry. We make two main contributions. First, we estimate the impact of price discrimination on revenue using a panel data and an instrumental variable approach. Second, we test comparative static predictions implied by the theory, on how exogenous markets 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 and this is despite the fact that we use a fundamentally different empirical approach, a different data set (a large fraction of the popular concert industry versus a single Broadway show), and that these two industries share few features beyond the fact that they both produce entertainment events. In addition, we find that the return to price discrimination increases in markets where demand is more heterogeneous, measured either by population density or demographic diversity. Finally, we find decreasing returns to additional seating categories.

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Figure 1. The frequency of price discrimination in the six cities with more than 300 concerts in the period 1992-2005.

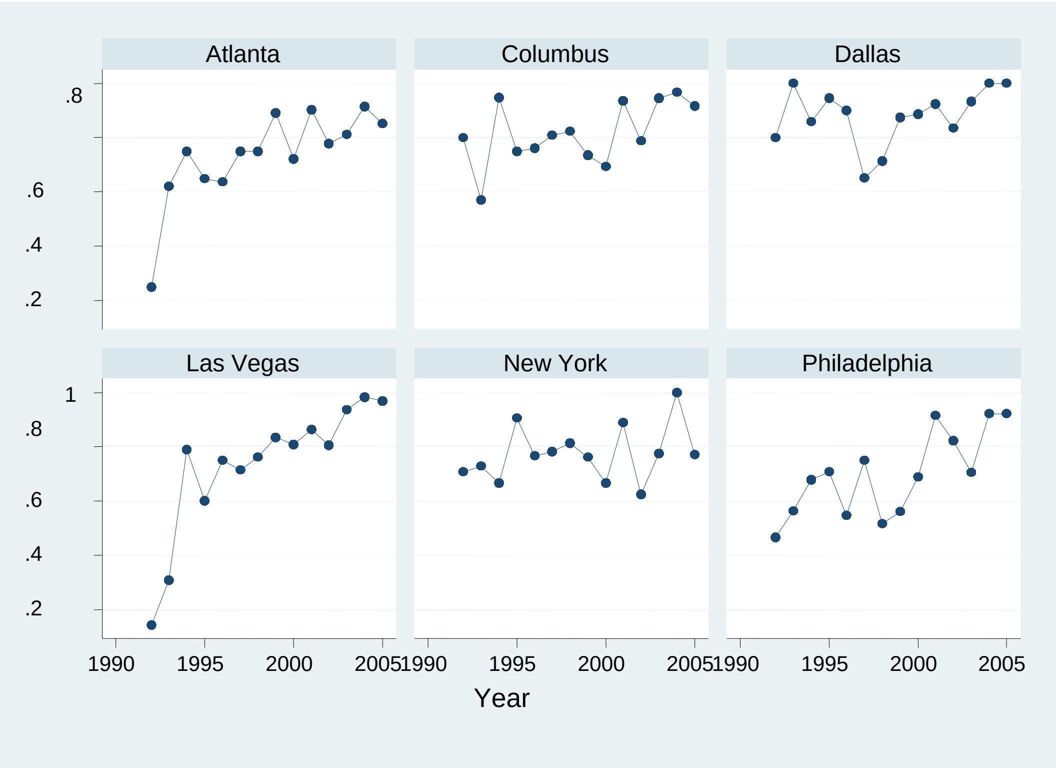

Figure 2. The frequency of price discrimination for the artists with more than 300 concerts in the period 1992-2005.

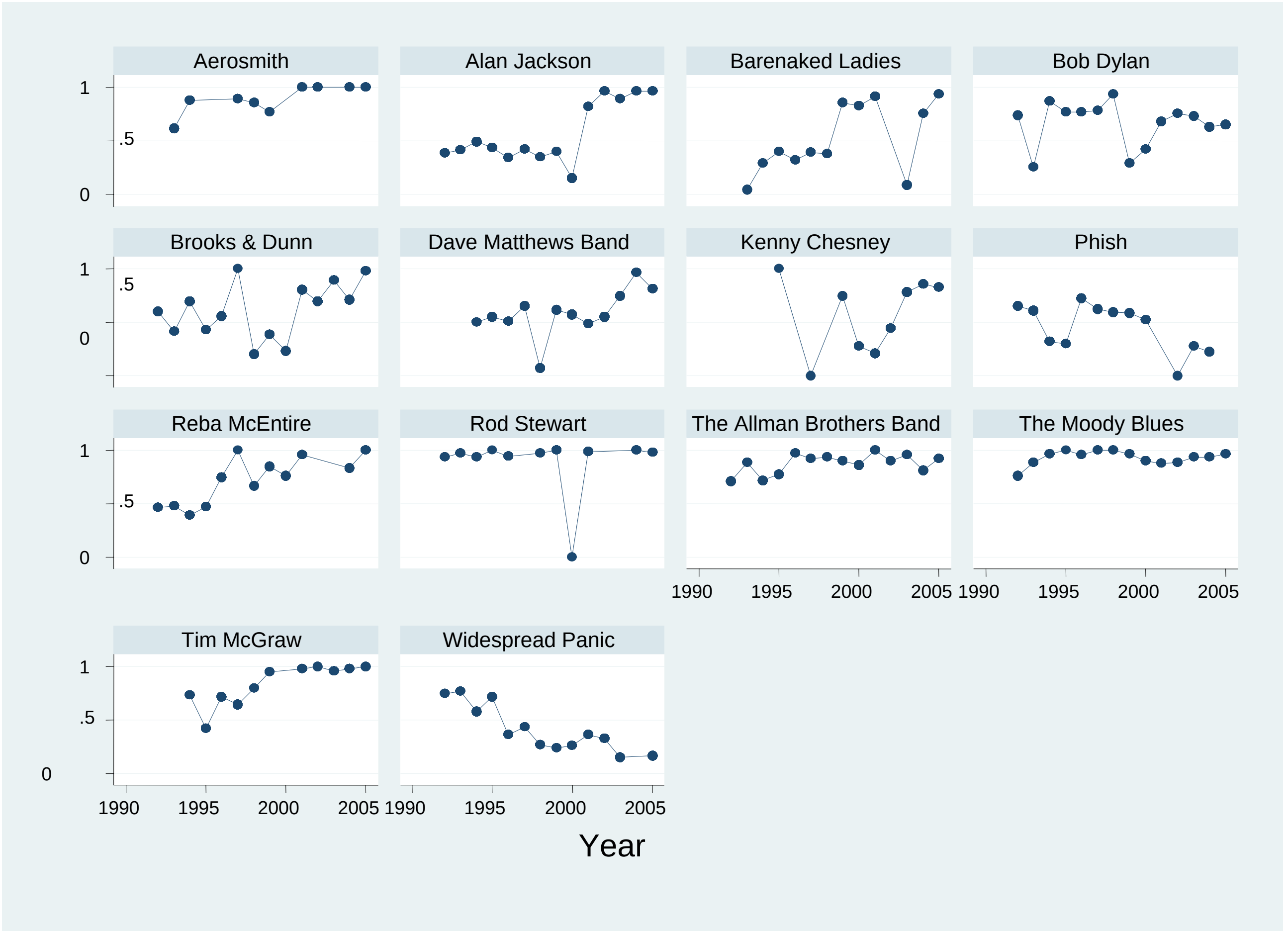

Figure 3. The frequency of price discrimination for the promoters with more than 350 concerts in the period 1992-2005 (and more than 8 years of continuous activity).

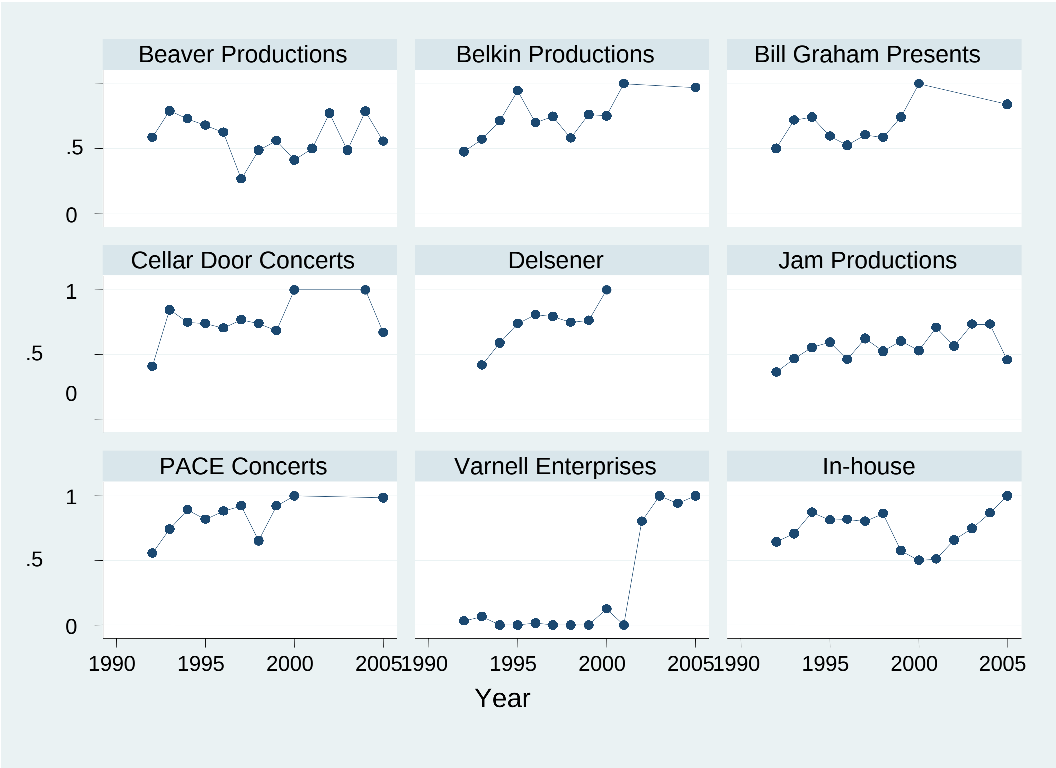

Table 1. Summary statistics (21,120 concerts)

Variable	mean	sd	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
N	21,120	21,120	21,120	19,540	19,540

Note: The dependent variable is the log of gross concert revenues. Robust standard errors in parenthesis, clustered by city in columns 1-3, by venue in columns 4 and 5.. * 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. Summary statistics (Instrumental Variables)

Variable	N	mean	sd	p10	p50	p90
Freq. of PD in the same city and year	15,314	.795	.297	.333	.937	1
Freq. of PD in the same city	18,894	.760	.276	.375	.857	1
Differences from the mean (for a given promoter)						
Freq. of PD in the same city and year	15,314	0	.248	-.326	.059	.231
Freq. of PD in the same city	18,894	0	.195	-.219	.026	.187

Note: the first two rows report summary statistics for the frequency of price discrimination for other concerts organized by the main promoter in the same city and year or in the same city (for all years in the sample). The table also reports summary statistics for the deviations of the two variables from the promoter-specific means.

Table 5. The impact of price discrimination on concert revenue (2SLS)

	(1) ln(revenue)	(2) ln(revenue)	(3) ln(revenue)
Price discrimination	0.090	0.068	0.074*
	(0.055)	(0.120)	(0.041)
ln(capacity)	0.937***	0.953***	0.942***
	(0.009)	(0.010)	(0.006)
Promoter f.e.?	No	Yes	No
Artist f.e.?	Yes	Yes	Yes
City f.e.?	Yes	Yes	Yes
Year f.e.?	Yes	Yes	Yes
Observations	15,314	15,314	18,894

Note: The dependent variable is the log of gross concert revenues. The instrumental variable in columns 1-2 is the frequency of price discrimination for other concerts organized by the main promoter in the same city and year. In columns 3, the IV is the frequency of price discrimination in other concerts by the main promoter in the same city (all years). Robust standard errors are in parentheses, clustered by city. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. First stage regression results (corresponding to the 2SLS results in Table 5)

	(1) Price discr	(2) Price discr	(3) Price discr
Freq. of PD in the same city and year	0.241***	0.114***	
	(0.027)	(0.026)	
Freq. of PD in the same city			0.336***
			(0.025)
F-test	F(1,319)=	F(1,319)=	F(1,386)=
(P-value)	77.15	20.01	179.74
	(0.00)	(0.00)	(0.00)

Note: First stage regression results corresponding to the 2SLS results in Table 5. The dependent variable is equal to one if price discrimination was used, zero otherwise. The table only reports the coefficients for the frequency of price discrimination for other concerts organized by the same promoter in the same city and year (column 1 and 2), or in the same city for all years (column 3). The F-test is the test of the significance of the impact of the excluded instrument. The critical value for the Weak-IV test based on the first stage F-statistic is 8.96. The null is that the instrument is weak, in the sense that the nominal 5% 2SLS t-test of the hypothesis that price discrimination does not affect revenue has size potentially exceeding 15% (Stock and Yogo 2005). Robust standard errors are in parentheses, clustered by city. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. The determinants of the return to price discrimination.

	ln(revenue)	ln(revenue)
Fixed effects		
Year f.e.?	Yes	Yes
Month f.e.?	Yes	Yes
Artist f.e.?	Yes	Yes
City f.e.?	Yes	Yes
Variables in Xi		
Ln (capacity)	0.975***	0.975***
	(0.021)	(0.022)
Number of artists	0.017***	0.009
	(0.005)	(0.014)
Number of promoters	0.044***	0.039***
	(0.008)	(0.015)
City competition		0.00040
		(0.0013)
Variables in Yi (interacted with indicator variable for price discrimination)		
Demand:		
Ln(Gini occupational heterogeneity index)	0.487**	0.561***
	(0.204)	(0.186)
Ln(Gini income heterogeneity index)	0.064	0.127
	(1.185)	(1.007)
Ln(Gini ethnical heterogeneity index)	0.063***	0.058**
	(0.025)	(0.023)
Average household income (/1,000)	0.003***	0.004***
	(0.001)	(0.001)
Population density(/1,000)	0.009***	0.011***
	(0.004)	(0.004)
City Population (/1,000,000)	0.023*	0.020
	(0.014)	(0.015)
Product:		
Ln (capacity)	-0.064***	-0.081***
	(0.019)	(0.019)
Age		0.055***
		(0.005)
Age^2		-0.00075***
		(0.00007)
Male ratio		-0.059*
		(0.031)
Prominence (words/1,000)		0.055***
		(0.009)
US band		-0.015
		(0.022)
Genre 1 (Rock)		-0.020
		(0.058)
Genre2 (Country)		-0.040
		(0.060)
Number of artists		0.007
		(0.013)
Number of concerts in current year (importance of the artist)		0.0032***
		(0.0003)
Price differential (Pmax-Pmin)		0.0007***
		(0.0001)

Competition:		
City competition		0.0026**
		(0.0013)
Distribution channel:		
Number of promoters		0.009
		(0.017)
Seasonality and trend:		
Year trend		0.0026
		(0.0031)
Month f.e.?	Yes	Yes
N	20,913	18,036

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

Table 8. 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
Observations	21,120	19,540	21,120

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