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Price discrimination in Broadway theater

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A common thread in the theory literature on price discrimination has been the ambiguous welfare effects for consumers and the rise in profit for firms, relative to uniform pricing. In this study I resolve the ambiguity for consumers and quantify the benefit for a firm. I describe a model of price discrimination that includes both second-degree and third-degree price discrimination. Using data from a Broadway play, I estimate the structural model and conduct various experiments to investigate the implications of alternative pricing policies. The observed price discrimination may improve the firm's profit by approximately 5%, relative to uniform pricing, while the difference for aggregate consumer welfare is negligible. Also, I show that the gain from changing prices in the face of fluctuating demand is small under the observed price discrimination.

1. Introduction

■ Price discrimination allows firms to increase their revenue above what may be obtained from uniform pricing. The impact on consumers is, in general, ambiguous. Although nonuniform pricing is common, its welfare implications are an empirical issue about which little is known. The goal of this study is to undertake an analysis of the welfare implications of price discrimination, using the example of Broadway theater. I present a model of individual consumer behavior and monopoly price discrimination, which is then estimated with data from a Broadway play. Using the estimated demand system, a range of counterfactual experiments are conducted to analyze the effects on welfare from price discrimination in this market.

The theoretical framework is a utility-based model of consumer behavior that incorporates characteristics suggested by the data and institutional details of the Broadway theater industry. The demand model is designed to be consistent with the observed behavior of the firm and includes both second-degree and third-degree price discrimination.[1] Setting different prices for different seat qualities is an example of second-degree price discrimination, or nonlinear pricing.[2] Discount mail coupons are targeted to consumers with lower willingness to pay, which provides an example

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[1] Tirole (1988) gives a thorough discussion of the different kinds of price discrimination. The analysis in this study would be the same regardless of whether I call it price discrimination, nonuniform pricing, or multiproduct monopoly pricing.

[2] Wilson (1993) provides a detailed account of the theory of nonlinear pricing. In this article, I use the terms nonlinear pricing and second-degree price discrimination interchangeably.

of third-degree price discrimination, or market segmentation. The sale of day-of-performance half-price tickets sold at a discount booth is modelled as a damaged good that further discriminates among self-selecting consumers.

The data consist of price and quantity sold for all 17 different ticket categories for all 199 performances of *Seven Guitars*, a play that ran on Broadway in 1996. The econometric specification of the behavioral model is a random-utility discrete-choice model with endogenously random choice sets. A virtue of using a structural econometric framework in this case is that a range of experiments can be performed using the estimated demand system. An empirical investigation of the welfare implications of price discrimination must rely upon an ability to analyze behavior with and without price discrimination, and to compute appropriate welfare measures. In the absence of data exhibiting both price discrimination and uniform pricing, it would not be possible to identify the difference in social surplus between uniform pricing and price discrimination without a behavioral model to form predictions. The experiments include uniform pricing, nonsticky prices over time, and abolishing the discount booth. In each case, comparisons are drawn with the benchmark scenario of the actual behavior of the firm and consumers.

Among the results, I find that the observed price discrimination increases the firm's profit by 5%, relative to a policy of optimal uniform pricing. The gain from price discrimination significantly depends on the magnitude of the discount offered for tickets sold at the day-of-performance discount booth. In particular, if the booth discount were 30% instead of 50%, firm profit would rise by 7%. From the point of view of consumers, the change in aggregate consumer surplus under price discrimination relative to uniform pricing is insignificant, though there is a redistribution of surplus among consumers. I also show the increase in profit from reoptimizing prices in the face of changing demand is less when a menu of several price alternatives is used than when a single price is used each period, which may help explain the presence of rigid price policies in this market.[3]

The empirical literature on price discrimination has evolved since the early 1990s. Borenstein (1991) and Shepard (1991) identify the presence of price discrimination from possible cost-based explanations for the observed price dispersion. Borenstein and Rose (1994) quantify a high degree of price dispersion due to price discrimination that is all the more interesting given the somewhat competitive nature of the industry they study (airline travel). A few more recent studies employ structural methods to investigate a variety of issues in relation to price discrimination—see Ivaldi and Martimort (1994), Bousquet and Ivaldi (1997), Cohen (2000), McManus (2001), Miravete (2002), Gary-Bobo and Larribeau (2004), and Verboven (2002). In the cultural economics literature, several researchers have analyzed theater demand and pricing, and two of these studies focus on the presence of multiple ticket prices. Huntington (1993) investigates whether revenue differs for theaters charging a range of ticket prices, over theaters that charge a single price for all tickets. In a theoretical study, Rosen and Rosenfield (1997) describe a model of ticket pricing that involves second-degree price discrimination. Finally, several previous studies have estimated price and income demand elasticities for the performing arts, as I do here also.[4]

The remainder of the article is organized as follows. Section 2 summarizes the data, with particular attention given to aspects that are incorporated in the model and the sources of price variation that serve to identify the demand system. Section 3 presents the behavioral model and the econometric model. Section 4 contains the results of the estimation, including the implied demand elasticities. Based on the estimated demand model, an array of experiments are explained and the results presented in Section 5. Section 6 concludes.

2. Summary of the data

■ "Broadway theater" refers to all plays and musicals performed in theaters in the Times Square region of Manhattan, New York City, with seating capacities in excess of 499. Typically,

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[3] Other industries that share similar features from this point of view include airlines, hotel accommodation, and sporting events.

[4] See Moore (1966), Felton (1992) and Lévy-Garboua and Montmarquette (1996).

the owner of a Broadway theater rents the theater to a show producer who decides, among other things, the ticket prices for the show. In contrast to most performing arts organizations, the objective of Broadway theater producers is to maximize profit. Ticket prices are not subject to any specific regulation. The majority of tickets are sold over the phone.[5] Some tickets are also sold at the box offices located at the theaters, or through a discount booth known as the TKTS. The Broadway play that is the focus of this study is *Seven Guitars*. Each Broadway show develops its own idiosyncratic approach to the marketing of the product; with respect to price discrimination, however, *Seven Guitars* is a typical example of behavior in the industry.[6]

Seven Guitars provides a good example of discriminatory pricing. There is little doubt that the price differences that are evident in a given performance cannot be explained by differing costs—the marginal cost of every ticket sold for a given performance is effectively zero. Moreover, while the number of seats in the theater presents a capacity constraint for the firm, suggesting the presence of a variable shadow cost of capacity, this constraint is rarely binding for *Seven Guitars*. With a maximum seating capacity of 947, the show sold out for 12 of the 199 performances, achieving an average attendance of 75% of capacity, or 707 people per performance (with a standard deviation of 157.15). Balcony seating is the only individual ticket category to be sold out in more than 12 performances, in that case selling out 23 times. Hence, congestion is not a significant issue in the data, although *ex ante* it might have been. The primary source of data for this study is the box office report for *Seven Guitars*, from which I observe price and quantity sold in each mutually exclusive sales category for every performance. In a single performance there could be attendees from all 17 categories, though on average only 8.7 of the categories are represented in a given performance. A total of 140,782 people saw the Broadway production of *Seven Guitars*.

An important distinction among ticket categories is between full-price tickets and discount-price tickets. Full-price tickets are for a specific area of seating, namely orchestra, mezzanine, rear-mezzanine, balcony, boxes, and standing room. These regions are differentiated by the average quality of the seating, or view, that is offered. All full-price options are available to all potential consumers and are sold via telephone. Discount-price tickets are available under various conditions. Some discount-price tickets are only available to individuals who receive a coupon in the mail or happen to come across one in a restaurant or some other chosen location. Another kind of discount, while available to all potential consumers, requires consumers to incur a non-pecuniary cost of having to wait in line at a discount booth. For discount-price tickets, the buyers are seated in the high-quality region of the theater, such as the orchestra, though generally not in the best seats within that region.

Table 1 presents summary statistics for prices, quantities, and revenues of each ticket category. The mean price for all ticket sales in all performances is $36.43 with a standard deviation of $15.11. The average Gini coefficient is .201 (standard deviation .040), indicating that the expected absolute difference between any two ticket prices selected at random is 40% of the mean price. By way of comparison, in a study of prices in the airline industry, Borenstein and Rose (1994) find an average (across flights) Gini coefficient of .181 (standard deviation .063), which implies that the expected absolute difference between any two fares selected at random is 36% of the mean fare.

□ **Price variation and demand identification.** Table 1 also indicates the different kinds of price variation that serve to identify demand. There are two types of price variation. First, prices vary across the different ticket categories. The mean price for orchestra tickets is $55.08. Other categories have lower average prices, such as the balcony with an average price of $16.93. The second type of price variation is changes over time (across performances) in the prices of each ticket category. This variation is reflected in the second column of numbers in Table 1, showing the standard deviation of prices for each ticket category.[7]

[5] Phone sales are through one of two phone-sales companies: Tele-charge and Ticketmaster.

[6] Based on conversations with several theater producers.

[7] The Manhattan Theatre Club (MTC) category has no price variation over time. This is a subscriber organization

TABLE 1 **Summary of Attendance and Revenues for Each Sales Category of *Seven Guitars***

	Price ($)		Attendance		Revenue ($)	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Full price						
Orchestra	55.08	4.22	162.74	77.22	9,112.29	4,765.14
Front mezzanine	55.08	4.23	40.04	41.70	2,262.27	2,462.55
Rear mezzanine	29.20	1.85	34.80	18.91	1,007.10	533.49
Balcony	16.93	4.91	38.60	17.26	679.26	421.85
Boxes	55.76	4.17	4.97	4.88	281.36	279.95
Standing room	22.27	2.55	6.14	4.50	134.77	96.24
Discount price						
10% off	49.40	3.88	6.71	5.55	335.74	286.61
Two-fer one	27.23	2.06	16.65	20.17	467.28	591.53
TKTS	27.53	2.11	158.87	71.29	4,358.12	1,956.91
MTC	22.00	0	258.99	60.28	5,697.71	1,326.18
AENY	50.36	1.81	3.81	2.46	193.07	128.17
Direct mail	39.51	2.28	48.43	36.80	1,925.78	1,461.92
Group	36.26	10.80	89.91	63.84	3,309.46	2,688.23
Student	26.21	2.01	68.35	56.38	1,775.98	1,440.68
TDF	16.46	5.81	153.72	90.67	2,306.93	1,163.35
Wheelchair	26.94	2.23	2.02	0.66	54.56	17.67
Complimentary	0	0	38.91	75.57	0	0

Notes: "Two-fer one" are two-for-one coupon sales. "TKTS" are tickets sold via the day-of-performance discount booths. "MTC" stands for Manhattan Theatre Club, which is a subscriber organization. "AENY" stands for Arts Entertainment New York, which is a private firm specializing in providing high-quality tickets to its customers. "TDF" stands for Theater Development Fund, which is a nonprofit organization that provides tickets to schoolchildren and so forth. In the model, "coupons" are the aggregation of all discount-price categories except TKTS, wheelchair, and complimentary tickets.

As usual with demand estimation, there is a question about the endogeneity of prices. What explains the observed variation in prices, and is it sufficient to identify the effect of price on demand? Consider first the price variation across the full-price ticket categories. The price of an orchestra ticket is higher than a balcony ticket because seat quality is higher in the orchestra than in the balcony. As explained in the next section, I estimate the different seat qualities in the demand system. Seat quality is therefore not contained in an error term, precluding this particular source of correlation between prices and a residual. But functional-form assumptions are now relied on to utilize this source of variation to identify the effect of price on demand.

Next, consider the time-series variation in prices for the full-price tickets. Prices for full-price ticket categories vary across performances due to predetermined peak-load pricing—performances for different times in the week are priced differently. For example, Saturday evening orchestra tickets are priced higher than Sunday matinee orchestra tickets. This price variation is decided by the producer prior to the first performance and is not changed over the life of the show. Analogous to the price variation across seat qualities, in this case I estimate time-of-week effects as part of the demand specification. Again, this precludes the usual endogeneity concern but limits identification of the price effect from this source of variation to rely on functional form.

While every seat in the theater may differ in quality, the firm used only three seat-quality categories for the purpose of setting different prices (at full price). But for most of the performances,

that formed an agreement with the producer of *Seven Guitars* for tickets to be available at $22 for certain performances. In the analysis, this category is aggregated with other coupon categories, as explained below.

only two quality categories were used. The medium-quality region was offered at a different price in only 50 of the 199 performances, the first time in the 133rd performance.[8] This provides a useful source of price variation. For a given seat quality, for given time-of-week, there is variation in the ticket price. Furthermore, although the introduction of the medium-quality tickets is correlated with the time trend (presumably it was done as a response to dwindling demand over time), the time trend is a smooth process, while this variation is discrete. For these reasons, variation in the availability of medium-quality tickets provides a useful source of price variation to identify the demand system.

There is also price variation in the discount-price ticket categories. Rather than attempt to estimate demand for all ten of the discount ticket categories, I distinguish only two types of discounts: coupon and booth. I define the coupon category as the aggregation of all discount categories except TKTS.[9] The key feature of the coupon category is that it includes all discount categories that are restricted to individuals who either received an actual coupon or are members of specific organizations or groups. That is to say, these categories are interpreted as a form of third-degree price discrimination.[10] Given this aggregation, the mean coupon ticket price in the data is \$31.01, with a standard deviation of \$8.71. The mean number of coupon tickets sold is 252.63, with a standard deviation of 167.62.

What explains the time-series variation in the coupon price? It is partly driven by time-of-week peak-load pricing, as with the time-series variation for the full-price tickets. But unlike the full-price tickets, day-of-week dummies explain relatively little of the variation in the coupon price. The coupon price variation is due mainly to the firm trying different ways of offering targeted discounts.[11] For example, targeted direct-mail coupons were used in the early performances, while two-fer one tickets were not introduced until midway in the show's run.[12] According to the producer of *Seven Guitars*, this variation in coupon availability reflects standard marketing practices for Broadway shows, rather than any deliberate technique for changing price in the face of fluctuating demand. In other words, there is some reason to view this source of price variation as being exogenous. To the extent that the time-series variation in the coupon price is not exogenous, the demand specification includes time-of-week dummies, a quadratic time trend, and a dummy for after the Tony Awards, which took place in the middle of *Seven Guitars*'s run. These variables should control for many of the obvious explanations of this price variation. The remaining variation in the coupon price over time may be an exogenous component.

The second type of discount is the booth ticket category, which corresponds to the TKTS category in the data. Below I explain the interpretation of this category. TKTS tickets were available for *Seven Guitars* in 197 of the 199 performances. The number of tickets made available at the TKTS booth varied from day to day, based on the number of unsold tickets up until the morning of the performance. In terms of price variation, note that booth tickets are sold at a 50% discount off the top full price (plus a \$2.50 service charge). Consequently, the same issues arise as with the price variation in the full-price ticket categories, described above.

In summary, there are several kinds of price variation in the data that serve to identify the demand system. Some of this variation is helpful only in conjunction with functional-form assumptions, which will be detailed in the next section. To what extent the particular functional-form assumptions used can be motivated by economic considerations will also be discussed in the next section. Meanwhile, there are other components of the price variation that should provide identification independently of functional form.

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[8] For the other 149 performances, these seats were included in the high-quality region. The medium-quality tickets are for the seats in the rear-mezzanine.

[9] I also exclude the wheelchair and complimentary tickets.

[10] An alternative interpretation is that coupons are a form of second-degree price discrimination. In that case, some consumers who see the show and had received a coupon, don't use the coupon. See Shaffer and Zhang (1995) for an analysis of coupon targeting.

[11] Most types of coupons are not limited to usage on certain days of the week. An exception is the MTC member coupons, which could not be used for Saturday evenings.

[12] Two-fer one coupons were placed in targeted locations, such as student cafeterias.

□ **Day-of-performance booth ticket sales as a damaged good.** The defining characteristic of booth ticket sales that I seek to incorporate in the demand model is that consumers must physically attend the booth on the day of the performance to purchase tickets. It is interesting that firms choose to sell tickets via this method. Despite having an effective telephone sales mechanism already available for the sale of tickets, the theater producer chooses not to use this mechanism for discount sales on the day of the performance, instead forcing consumers to incur the disutility associated with purchasing a ticket at the booth. I interpret this ticket category as a deliberately damaged version of the product. The firm chooses to make the good less attractive than it would otherwise be. This would be an example of a damaged good, as modelled by Deneckere and McAfee (1996).

However, the conventional damaged-goods explanation is not entirely adequate in this case, for the following reason. There is actually significant variation in seat quality within the orchestra region of the theater, which I discuss below. Despite this quality variation, there is no variation in price for full-price tickets in the orchestra (for a given performance).[13] One consumer may buy a full-price ticket over the phone for the orchestra, pay $55 and get the best seat in the orchestra. Another consumer may also buy a full-price ticket over the phone for the orchestra, pay $55 and get the worst seat in the orchestra. While this may seem puzzling, note that discount ticket purchasers will generally obtain a seat in the orchestra. In particular, booth ticket buyers (i.e., TKTS sales) tend to be seated in the orchestra, typically in the lower-quality seats within the section. Hence, there is variation in prices paid by people seated in the orchestra at a given performance, but this is due to the pricing of discount ticket categories rather than variation in the price of full-price tickets.

An alternative to selling booth discount tickets and seating the buyers in the orchestra would be to subdivide the orchestra into high- and low-quality seats, set two different prices, and sell tickets over the phone.[14] This would accomplish the same goal in terms of having multiple prices for orchestra seats and using quality differences to facilitate sorting of consumers. Moreover, this alternative may be preferred, since consumers are not required to incur any disutility from having to line up at a booth on the day of performance, providing a greater overall surplus. To provide a justification for the firm preferring booth ticket sales over orchestra subdivision, I allow for the possibility that the disutility of attending the booth depends on consumers' willingness to pay for seat quality (i.e., their income).[15] By incorporating type-dependent disutility into the damaged-goods framework, there is now the potential for the firm to prefer booth ticket sales over orchestra sbudivision. While booth ticket sales and orchestra subdivision would provide tickets in the lower-quality seats within the orchestra, the booth has the added advantage of being even less attractive to high-income people.[16]

□ **Other data.** In addition to the price and quantity data described above, I observe variables that help to capture shifts in demand for *Seven Guitars*. This includes advertising, the Tony Awards, and the number of other Broadway shows, which I now explain.

A total of $878,337 was spent on advertising *Seven Guitars*, amounting to 20% of the show's running costs, or an average of more than $30,000 per week during the 25 weeks of performances. The disaggregated data covers advertising in newspapers, magazines, travel guides, and theater guides; on billboards and bus shelters; on radio; and on cards in restaurants. The majority of advertising expenditures was with *The New York Times* (63%), mostly as graphical display advertisements in the Sunday edition (30%). For the purpose of this study the data are

[13] Prices do vary from performance to performance.

[14] There could be multiple subdivisions of the orchestra, and multiple prices, the point is the same.

[15] It is important that the model incorporate an explanation for why the firm would prefer booth ticket sales, otherwise it would be inconsistent with a key institutional feature of the industry.

[16] Another possible reason to prefer booth sales is because the number of tickets made available at the booth is determined on a daily basis and depends on the number of full-price sales prior to the day of performance. In this way, the booth ticket category provides a fairly low-cost and effective way of determining when to increase or decrease the number of discount tickets to offer for a given performance.

aggregated into a scalar variable intended to measure the daily level of advertising. I take the level of advertising for each separate form of advertising to be equal to the dollar expenditure.[17] To correct for the fact that a particular advertisement is seen by people on days other than the first day it appears, each advertising expenditure is uniformly distributed over the duration of the publication.

Once an individual has been exposed to an advertisement, or several advertisements, there may be a time lag until the individual contacts the box office, or more correctly Tele-charge, which handled telephone bookings for *Seven Guitars*. There will typically be a further time lag between the time of booking and the time this person attends a performance. This suggests that attendances during a given week may depend upon advertising over the previous month, say. For this reason, the advertising variable that is used in the empirical analysis is a moving average of the daily advertising expenditures over the last 28 days. There is a question about the endogenous nature of advertising. This is analogous to the discussion of the price variation above, in which the variation may be explained by day-of-week dummies and a time trend. Hence, the variation in the advertising variable may add explanatory power when combined with functional-form assumptions.

Seven Guitars was performed in the Walter Kerr theater, and I use information on the seating in this theater for the estimation. In particular, the manager of the box office at the Walter Kerr assigned every seat in the theater a rating from one to ten, based upon his experience of people's preferences when buying tickets, to reflect the quality of the view from each seat. From this procedure it is apparent that there is significant variation in seat quality within the area deemed as the high-quality region, while for the medium-quality and low-quality regions there is insignificant variation in seat quality across seats within each of the regions. The capacity of the high-quality region is 755; for the medium-quality region it is 126; and for the low-quality region it is 66.

From *Variety* magazine I have weekly information on the attendances for every other Broadway show that was performing during the same period as *Seven Guitars*. Such data may capture shocks from tourism, the weather, and other peculiarities that might affect Broadway attendance. For the 25-week period that *Seven Guitars* was performed, there were an average of 15.6 musicals and 9.0 plays performing on Broadway. During the same period, the average weekly total attendance for all Broadway shows was 200,839.87 (standard deviation of 20,256.48). With almost all shows being performed eight times a week, this amounts to an average of 25,105 people attending Broadway theater each night in New York.

Income is an important dimension of consumer heterogeneity in the demand system presented in the next section. The producers of *Seven Guitars* chose not to advertise nationally in order to encourage more tourists to see their show, because such an investment is believed to be worthwhile only for longer-running shows. I consider the potential consumers in this case to be a subset of all people in the New York metropolitan region, including tourists to the area. In particular, it is assumed the potential consumers for a given performance of *Seven Guitars* are all people who attend Broadway theater at the same time. The League of American Theatres and Producers (2001) surveyed Broadway audiences in the 1990–91 season, obtaining data on family income for 7,281 people attending a sample of performances across 12 different shows.[18] From that survey the proportion of people whose annual family income lies within certain intervals is known, as reported in Table 2.

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[17] This reflects the principle of the marginal dollar spent on each form of advertising on any given day having an equal effective advertising value, while ignoring the advertising value of inframarginal expenditures (and the fact that some categories will be zero on some days).

[18] As far as I know, the survey was done by providing all Broadway patrons, over a period of a about a month, with a questionnaire and return mail envelope. No information was available on the response rate. The main advantage of the survey is that it provides information on the people who attend Broadway theater. As explained in the next section, in my analysis I consider the behavior of people who attend Broadway theater, not of New York more generally. Other alternative data, such as the distribution of income in Manhattan, may not be very relevant for Broadway.

TABLE 2 **Distribution of Annual Family Income and Estimated Parameters for the Log-Normal Distribution of Income**

Income Interval		Percent
Less than $25,000		5.7
$25,000 to $34,999		10.3
$35,000 to $49,999		14.3
$50,000 to $74,999		26.7
$75,000 to $99,999		16.2
$100,000 to $149,999		15.2
$150,000 and above		11.6
Number of respondents		7,281
Estimated parameters		
Mean	11.3483	(.8248)
Standard deviation	.7937	(.7092)

Notes: Data are from The League of American Theatres and Producers (1991). Income is measured in November 1990 dollars. Estimated parameters are for the underlying normal distribution of the log-normal distribution of income. Standard errors are in parentheses.

3. Structural econometric model

■ **Behavioral model.** Consumers are presented with a menu of different ticket options for seeing a play, or not. There are various tickets for specific seat qualities or views within the theater, and there are various discounts. Different prices for different seat qualities is an example of second-degree price discrimination, and different prices for individuals with coupons is an example of third-degree price discrimination. It is assumed that each consumer can choose among the ticket options for a single performance only, which rules out intertemporal substitution.[19]

Individuals are differentiated along two dimensions: income and their taste for this play relative to the outside alternative. Let $y_i \geq 0$ denote the income of consumer i, and let $\xi_i \geq 0$ denote consumer i's relative taste for the outside alternative (higher ξ_i means a higher valuation of the play). As a matter of interpretation, ξ_i can also be thought of as the individual's perception of the quality of the show and may depend on numerous aspects.[20] Hence, each individual is characterized by the pair (y_i, ξ_i). Both y_i and ξ_i are known to the individual but unobservable to the firm. Income is distributed according to the cumulative distribution function $F(y)$, and taste is distributed according to the cumulative distribution function $G(\xi)$. Both distributions are known to the firm. For simplicity, F and G are assumed to be independent.[21]

Consistent with the data, I allow for three quality-differentiated full-price ticket options. The three regions are labelled high quality, medium quality, and low quality. All individuals prefer higher-quality seats but differ in their willingness to pay for higher quality. As previously discussed, all seats in the high-quality region of the theater do not provide equivalent seat quality. Indeed, there appears to be fairly significant variation in quality within the high-quality region, which is likely to play an important role in consumers' decision making. For the low-quality and medium-quality categories, the assumption of equal seat qualities within each region is a good approximation. Each quality region also has a capacity constraint.

[19] This is mainly done for computational tractability purposes. However, the restriction also enhances identification of the demand system by providing variation at the performance level. An alternative would be to allow consumers to choose over performances in a whole week, in which case variation is limited to the weekly level.

[20] For a detailed discussion on the perception of show quality in relation to the demand for theater, see Throsby (1990).

[21] As discussed below, the outside alternative is seeing another Broadway show. The independence assumption means that income and the taste for this particular play are uncorrelated.

The presence of both capacity constraints and quality heterogeneity within the high-quality region lead me to incorporate rationing in the model by arranging consumers in a random sequence. Specifically, M potential consumers are in a random sequence $\{(y_1, \xi_1); \ldots; (y_M, \xi_M)\}$. Following the order of the sequence, consumers are individually presented with their choice set, and depending on their decision the choice set for the next consumer in the sequence may be modified—an option may be removed because a capacity constraint has been reached, or the best available seat in the high-quality region may have a lower quality. Consequently, the seat quality that is offered to individual i in the high-quality region depends on the number of seats in the high-quality region that are sold to individuals ahead of individual i in the sequence.[22] Let q_{ih} denote the quality of seat, or view, that is associated with the high-quality, full-price ticket option for individual i, and let $q_{im} \equiv q_m$ and $q_{i\ell} \equiv q_\ell$ denote the seat quality for medium-quality and low-quality full-price ticket buyers.

Subject to availability, the net utility to individual i from choosing a full-price ticket for seat quality $j \in \{\ell, m, h\}$ is given by

$$U_{ij} = q_{ij}[B(y_i) - p_j]^\eta, \tag{1}$$

in which $B(y_i) \leq y_i$ is individual i's budget for entertainment expenditures, p_j is the price of the ticket, and η is a parameter.[23] With this formulation, consumers' marginal utility from seat quality depends on their level of income, leading to a self-selection process in which high-income individuals choose high-quality seats and low-income individuals choose low-quality seats. The function B contains parameters that allow me to estimate the appropriate proportion of income that is relevant for individuals' entertainment expenditure decisions.[24] I use a specification that allows for wealthier people to spend a greater absolute amount of income on entertainment, but a lower proportion of their total income than less-wealthy individuals. Specifically,

$$B(y_i) = \delta_1 y_i^{\delta_2},$$

where $\delta_1 > 0$ and $\delta_2 \in (0, 1]$ are parameters. Individuals first decide how much income to allocate to entertainment and perhaps other categories such as clothing, travel, savings, and so forth, and then subsequently decide how to spend their entertainment budget on the various possibilities that include this play.[25] I assume the δ parameters are the same for all individuals (i.e., conditional on income there is no unobserved heterogeneity in budgeting).[26]

In addition to the above full-price ticket options, with probability $\lambda(y_i|\gamma)$ consumer i receives a coupon that can be used to purchase a ticket for a high-quality seat at price $p_c < p_h$ and obtain utility

$$U_{ic} = q_{ih}[B(y_i) - p_c]^\eta.$$

The density $\lambda(y_i|\gamma)$ is the outcome of some coupon technology available to the firm. The parameter γ corresponds to the efficiency of the coupon technology (i.e., how accurately coupons are targeted to low-income individuals).[27]

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[22] I assume seats are allocated in order of best to worst.

[23] An alternative to the functional form in (1) is an additively separable specification. However, for such utility functions, in the presence of a continuous distribution of consumer types, a revenue-maximizing firm typically prefers to offer only the high quality good. With this specification, in general, the firm optimally chooses to offer many different quality levels. Note also the model does not allow consumers to decide when they will see the play.

[24] An alternative approach is to include a coefficient on price that would increase the disutility of price.

[25] One set of assumptions that would permit two-stage budgeting in this context is if the overall utility function were additively separable in the utility from consuming entertainment, and if the prices of all goods in the entertainment category moved in proportion to one another. See Deaton and Muellbauer (1980).

[26] This may not be a restrictive assumption for the following reason. Income is already a form of unobserved heterogeneity in the model and I use separate data to estimate the distribution of income. The budget equation then transforms the income distribution to help explain observed attendances. Allowing for additional unobserved heterogeneity in the budget equation would provide greater flexibility, but the current function is already a quite flexible transformation.

[27] Although each individuals' level of income is private information, the firm contracts a third party, which possesses private signals about each individual's level of income, to disseminate coupons.

Consumers also have the choice of going to a discount booth where they can purchase a ticket for one of the high-quality seats that remain after all individuals have had an opportunity to purchase a full-price seat. The booth ticket quality is denoted as q_{ib}. I assume there is a time cost for having to physically attend the booth.[28] In particular, the utility from purchasing a booth ticket is given by

$$U_{ib} = q_{ib}[B(y_i) - p_b - \tau(y_i)]^{\eta},$$

where $\tau(y_i) \geq 0$ is an increasing function that represents the time-cost of attending the booth. I adopt a simple linear specification for the cost of attending the booth. As described in Section 2, the essential feature is for this cost to depend on individuals' income levels:

$$\tau(y_i) = \tau_1 y_i + \tau_2,$$

where $\tau_1 \geq 0$ and τ_2 are parameters to be estimated.[29]

To complete the choice set I specify the utility from the outside alternative.[30] The goal here is to provide a specification that acts as a reduced-form valuation of the highest utility that may be obtained from seeing another show, and that also gives rise to sensible substitution patterns. I assume the utility from the outside option is given by

$$U_{io} = \xi_i^{-1}[B(y_i) - p_o]^{\eta_o},$$

where p_o is the price of the outside option and η_o is a parameter. Individual consumers' tastes for *Seven Guitars* relative to seeing another show are captured by ξ. I divide the outside utility by ξ_i (higher values of ξ_i imply lower willingness to see a show other than *Seven Guitars*), but I could equally have written ξ_i to multiply the utilities of each inside alternative. By including heterogeneous valuations of the outside alternative, the aim is to partially capture the presence of competing firms.[31] Doing so requires not only that the value of the outside alternative be correlated with the value of the inside alternatives, but that individuals also vary in their relative taste for the outside option—as if the outside alternative represents a set of vertically differentiated seat qualities for a horizontally differentiated show.[32]

To summarize, the utility for individual i from product j, assuming this individual received a coupon, is given by

$$U_{ij} = \begin{cases} q_{ij}[B(y_i) - p_j]^{\eta} & \text{for } j \in \{\ell, m, h\} \\ q_{ih}[B(y_i) - p_j]^{\eta} & \text{for } j = c \\ q_{ij}[B(y_i) - p_j - \tau(y_i)]^{\eta} & \text{for } j = b \\ \xi_i^{-1}[B(y_i) - p_j]^{\eta_o} & \text{for } j = o.\text{cr} \end{cases}$$

[28] From the data, $q_m \leq q_{ib}$ for all i, while $p_b = p_m$. The time cost is needed to provide an incentive for individuals to choose medium-quality, full-price tickets over booth tickets that are the same price and for higher-quality seating.

[29] As with the budget equation above, I assume there is no additional unobserved heterogeneity in this cost specification. For the same reasons I would argue that this is of little consequence.

[30] As previously noted, the outside alternative is to see another Broadway show. The main reason for interpreting the outside alternative in this relatively narrow way is that I have data on the number of people who attended Broadway theater at the same time that *Seven Guitars* was on Broadway. Hence, given this interpretation, I observe the number of individuals who in fact chose the outside alternative.

[31] The common practice in discrete-choice demand models is to normalize the utility of the outside alternative to zero. For vertically differentiated products, however, zero-outside utility implies unreasonable substitution patterns. For example, if the relative value of the outside alternative increases by a small amount, then a zero-outside utility normalization implies that consumers switch out from the low-quality-inside alternative only. In reality, consumers would switch from the high-quality-inside option to the outside option also.

[32] In this respect I draw on the approach of Stole (1995), who provides a theoretical analysis of oligopoly nonlinear pricing in which individuals similarly possess both horizontal and vertical preference heterogeneity.

If an individual did not receive a coupon, his utility function is the same except that it excludes choice $j = c$.[33] The expected demand for tickets in category j is equal to

$$S_j(\cdot) = M \int_{(y,\xi)\in A_j} dF(y)dG(\xi),$$

where A_j is the set of consumer types who most prefer option j and, as noted above, I assume F and G are independent. More formally,

$$A_j = \left[(y_i, \xi_i) : U_{ij} \geq U_{ik}, \forall k \in \Omega\right] \subset \Re^2_+,$$

where $\Omega = \{\ell, m, h, c, b, o\}$.

I defer the explanation of the firm side of the the model to the section on counterfactual experiments (Section 5), where it is used. I make no assumptions on the firm's behavior that are incorporated in the estimation of the demand system. This helps to limit the possible sources of misspecification in the estimated model, with a potential efficiency loss.

□ **Econometric model.** The behavioral model described above is an example of a discrete-choice random-utility model with endogenously random choice sets.[34] The model is estimated using a maximum-likelihood estimator. I now detail distributional and other assumptions that are needed for estimation of the econometric specification of the behavioral model.

The distribution of potential consumers' income is estimated based on the survey by the League of American Theatres and Producers. The data consist of the proportion of people attending Broadway theater in 1990–91 with annual family income within n intervals. The intervals are inflated to 1996 levels using the Consumer Price Index, and a log-normal distribution is fitted using a minimum distance estimator. The results are reported in Table 2. Estimated mean annual family income is $116,225 (in 1996 dollars).

The distribution of individuals' tastes for the show may change from performance to performance. I assume an exponential distribution,

$$\xi_{it} \sim \exp(X_t\beta),$$

in which the vector $X_t = \{$constant, advertising, dummy for before the Tony Awards, various day-of-performance dummies, number of other Broadway shows in the same week, time$\}$, and β is a parameter vector.[35]

For the probability density of receiving a coupon I assume the following specification:

$$\lambda_{it} = 1 - \frac{\exp(\alpha y_i - Z_t\gamma)}{1 + \exp(\alpha y_i - Z_t\gamma)},$$

where $Z_t = \{$constant, dummy for performances when Manhattan Theatre Club members were allowed to attend, various day-of-performance dummies, time, time-squared$\}$ is a vector of data. This density has the appearance of a backward "s" for $\alpha > 0$, with the probability of receiving a coupon decreasing in y_i. The vector γ is a parameter vector representing the number of coupons the firm sends out. I interpret the scalar α as a coupon efficiency parameter—higher values of α

[33] Or equivalently, assume $U_{ic} \equiv 0$.

[34] The choice sets are random because an individual has a coupon with only a certain probability. In addition, the choice sets are endogenous because the choices available to an individual depend on the optimal choices of individuals ahead in the sequence.

[35] For simplicity, the income and taste distributions are independent. Since the outside alternative is to see another Broadway show, it seems reasonable to believe that income and the taste for this particular play would be uncorrelated. Note also, the advertising variable is a moving average of the past 28 days' advertising expenditures, as explained in Section 2.

imply a less-efficient coupon technology (that is, a greater probability of wealthy people receiving a coupon).

The capacities of the three seating regions are denoted by C_ℓ, C_m, and C_h. Once the capacity of any region is reached within a sequence of simulated consumers, the option is no longer available for subsequent individuals in the sequence. Let k_{ijt} denote the number of tickets purchased by consumers ahead of individual i (in the sequence) for region j in performance t. Then tickets for category j are only in the choice set if $k_{ijt} < C_j$. To compute the seat quality in the high-quality region of the theater that is offered to individual i, I use the distribution of rankings and assume the difference between consecutively ranked seats within the high-quality region is the same, no matter what their rankings. Since the high-quality region adjoins the medium-quality region, I also assume the medium quality is uniformly different from the worst seat in the high-quality region. For the low-quality seats, I allow for an arbitrary difference in quality, since these seats are physically separate in the upper balcony. Given these assumptions, I therefore estimate the quality of the best seat in the house ($Q_{\max}$), the medium-quality level (q_m), and the lowest-quality seat (q_ℓ).

Conditional on an individual receiving a coupon, the utility specification that is the basis for estimation is given by

$$U_{ijt} = \begin{cases} q_{ijt}(\delta_1 y_i^{\delta_2} - p_{jt})^{\eta} & \text{for } k_{ijt} < C_j \text{ and } \quad j \in \{\ell, m, h\} \\ q_{iht}(\delta_1 y_i^{\delta_2} - p_{jt})^{\eta} & \text{for } k_{ijt} < C_h \text{ and } j = c \\ q_{ijt}(\delta_1 y_i^{\delta_2} - p_{jt} - \tau_1 y_i - \tau_2)^{\eta} & \text{for } k_{ijt} < C_h \text{ and } j = b \\ \xi_{it}^{-1}(\delta_1 y_i^{\delta_2} - p_j)^{\eta_o} & \text{for } j = o. \end{cases}$$

If the individual does not receive a coupon, the utility function does not include the choice $j = c$. The choice set for each individual is random, depending on the exogenous probability of receiving a coupon and the endogenous behavior of other individuals in the market.

The set of parameters to be estimated is

$$\Theta = \{q_\ell, q_m, Q_{\max}, \delta_1, \delta_2, \tau_1, \tau_2, \eta, \eta_o, p_o, \alpha, \beta, \gamma\}.$$

Noting that the distribution of individuals' income is separately estimated, the predicted market share of product $j \in \Omega$, in period $t \in \{1, \ldots, T\}$, conditional on all parameters, is computed by

$$s_{jt}(p_t, X_t, Z_t, \Theta) = \int_{(y,\xi)\in A_{jt}} dF(y)dG(\xi \mid X_t\beta), \tag{2}$$

where

$$A_{jt} = \left[(y_i, \xi_i) : U_{ijt}(p_t, X_t, Z_t; \Theta) \geq U_{ikt}(p_t, X_t, Z_t; \Theta), \forall k \in \Omega\right].$$

For notational ease, the specification shown in (2) suppresses the integration over realizations of the coupon distribution and available capacity. Denote the actual number of individuals who choose option j in period t as N_{jt}, where the number of individuals choosing the outside alternative is determined by

$$N_{ot} = M_t - \sum_{j\in\Omega\setminus\{o\}} N_{jt}.$$

The market size, M_t, is the total number of people attending Broadway theater in the same week divided by eight (the weekly number of performances for all Broadway shows). The log-likelihood function can now be stated:

$$\ell(\cdot, \Theta) = \sum_{t=1}^{T} \sum_{j \in \Omega} N_{jt} \log s_{jt}(\cdot, \Theta). \tag{3}$$

The vector of estimated parameters is the value of θ that maximizes (3).

In Section 2 I described the different kinds of price variation contained in the dataset. I argued that some of the price variation helps to identify the demand system without relying on functional-form assumptions. Meanwhile, other kinds of price variation provide identification only when combined with functional-form assumptions. Consider full-price high-quality tickets, for example. The price of a high-quality seat, p_{ht}, varies across days of the week, and day-of-performance dummies are included in both X_t and Z_t. The effects of each of these three time-varying components are identified separately because each enters nonlinearly in different parts of the model. Two factors support this approach. First, the functional form has been motivated by a behavioral model. In particular, the separate nonlinear components are motivated by distinguishing the utility function from roles played by the distributions of individual heterogeneity (tastes and coupon availability).[36] Second, there still remains some variation in the data that provides identification without relying on functional form.

In the econometric model, as in the behavioral model, the only sources of uncertainty are from the individuals' unobserved heterogeneity. There is no additional logit, probit, or other such error term. All of the stochastic elements in the econometric model have specific interpretation within the behavioral model. This limits the model's ability to explain discrepancies between predicted behavior and actual behavior.[37] To compute the optimal parameter values, I use a nonderivative simplex search algorithm. The random sequences are simulated, which introduces a source of bias to the maximum-likelihood estimator.[38]

4. Empirical results

■ To estimate the model, several normalizations are imposed. The quality level of the low-quality seats is set equal to one ($q_\ell = 1$). It appears from the estimation that η and η_o are not separately identified, while the difference between the two parameters is identified. I therefore set $\eta_o = 1$. Since I have no data on the number of coupons that were sent out, I set the value of α to .01 (robustness checks are discussed below). Lastly, the price of the outside alternative appears to be poorly identified by the data, so this is set to zero, $p_o = 0$.[39] The remaining 28 parameters are estimated. Observations for the opening night of *Seven Guitars* are not used in the estimation, since the large number of complimentary tickets on that night (572) suggests an aberration. This leaves 198 performances.

The estimated parameters are shown in Table 3. The quality parameters, q_m and $Q_{\max}$, should

[36] Of course, there remains a degree of arbitrariness even in the behavioral model. The point is, the model offers a clear context and explanation for the specific functional form.

[37] An unlikely data point in the current model can be explained by either the uncertainty of income or the uncertainty of the taste for the play. Adding an additional error term would be a generalization that provides another source of explanation for an unlikely data point and will have the effect of smoothing the likelihood function. Whether additional error terms would improve the model is not clear. An implication of the limited sources of error in the model is the low standard errors that arise from estimation in the next section.

[38] The bias is mitigated by using a large number of simulation draws of the random sequences. The reported estimates were computed based on 1,000 draws. See Pakes and Pollard (1989) and McFadden (1989) on the use of simulation methods with extremum estimators such as that used here.

[39] Since I have no comparable data on the price of the outside alternative, I must estimate or normalize p_o. If the actual price of the outside alternative is correlated with the ticket prices for this show, as one might expect, then normalizing the price of the outside alternative will lead me to underestimate the sensitivity of aggregate demand to price changes. It may be possible to allow p_o to depend on the day of the week, which could alleviate this concern. However, note that the distribution of ξ, which affects the utility of the outside alternative, does already depend on the day of the week, helping to mitigate this potential problem.

TABLE 3 Estimated Parameters

	q_m	1.6921	(.0064)
	Q_{max}	3.3314	(.0244)
	δ_1	2.5199	(.0163)
	δ_2	.4414	(.0007)
	τ_1	.0067	(.0000)
	τ_2	2.7365	(.0305)
	η	1.0316	(.0022)
β:	Constant	.0180	(.0006)
	Advertising ($'00,000)	.0100	(.0005)
	Tony Awards	.0008	(.0002)
	Saturday evening	.0307	(.0015)
	Friday evening	.0080	(.0010)
	Sunday evening	.0237	(.0038)
	Sunday matinee	.0045	(.0016)
	Saturday matinee	.0040	(.0004)
	Thursday evening	.0050	(.0011)
	Number of other shows	.0094	(.0001)
	$t/100$	.0525	(.0008)
γ:	Constant	21.2021	(.1045)
	Manhattan Theatre Club	−.8105	(.0406)
	Saturday evening	−3.1797	(.1322)
	Friday evening	−1.9682	(.1144)
	Sunday evening	.6080	(.6669)
	Sunday matinee	−.2090	(.0879)
	Saturday matinee	−.1995	(.0820)
	Thursday evening	−.3824	(.1284)
	$t/100$	−4.4849	(.0635)
	$t^2/10,000$	−.0653	(.0076)
	Number of observations		4,886,572
	Log-likelihood		−776,703.44

Notes: Standard errors are in parentheses. The following normalizations were applied: $q_l = 1$, $\eta_o = 1$, $p_o = 0$, and $\alpha = .01$. Advertising is a moving average over the previous 28 days.

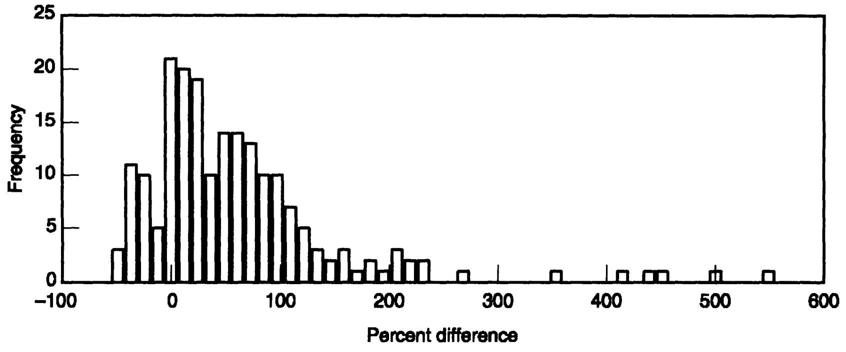
be gauged with respect to the normalization for q_ℓ. The estimates imply that the best seat in the house is 3.3 times better than the worst seat in the house. With the typical prices of $15 for low-quality seats and $55 for high-quality seats, highest-quality buyers pay 3.66 times more for a seat, that is, 3.3 times higher quality. At the mean weekly income level of $2,227.10, the implied budget for entertainment expenditures is $75.69, or 3% of weekly income. The cost of attending the booth is implied by the parameters τ_1 and τ_2. The type-dependent component of the cost depends on τ_1, with the estimated parameter implying that the cost of attending the booth rises by almost .7 of a cent for every additional dollar of weekly income. Thus, for example, the cost of attending the booth for an individual with the mean level of family income is estimated to be $12.11, which seems reasonable.[40]

The estimated parameters for the distribution of individuals' taste for this play are given in Table 3 under the heading of the β parameters. Recall that I use an exponential distribution; hence, for example, the dummy for the Tony Awards increases the mean (variance) of the distribution by .01 (.0001). Though the positive time trend was not anticipated, the advertising and Tony

[40] The booth ticket price variable includes the service charge of $2.50. Consequently, the estimate of $\hat{\tau}_2 = 2.74$ ought not be gauged by its closeness to 2.50.

FIGURE 1

PERCENTAGE DIFFERENCE: PREDICTED AND ACTUAL FULL-PRICE, HIGH-QUALITY TICKET SALES



variables would explain the drop in attendances after the Tony Awards. The γ coefficients explain movements in coupon sales. While almost all parameters are extremely accurately estimated and significant, several of the γ parameters are not.

As a check on how informative the X and Z variables are for explaining variation in demand, I reestimate the model without these variables. That is, I impose the restriction that the coefficients on these variables are all zero. The likelihood-ratio test overwhelmingly rejects the hypothesis of zero coefficients. As an indication of the differences in the fit of the model with covariates versus the fit of the model without covariates, the mean absolute percentage differences in predicted sales for each ticket category are: 26% (low quality), 154% (medium quality), 23% (high quality), 64% (coupons), and 49% (booth tickets). To help assess the fit of the model (with covariates), Figures 1 to 4 present the differences between predicted and actual behavior. In Figure 1 are the percentage differences between the number of predicted high-quality ticket sales and the actual number of high-quality sales for each performance. It is apparent that the model predicts high-quality sales to within roughly 50% of the actual number in a large proportion of performances, while also exhibiting a tendency to overpredict. The equivalent figures for low-quality, booth, and coupon sales appear as Figures 2, 3, and 4, respectively. Of these cases, booth and coupon sales appear to be the best-predicted ticket categories, with the majority of performances predicted to within roughly 50% of the actual number of sales.

The reason why the model tends to overestimate demand is related to the presence of the capacity constraints. For some observations, the estimated model overpredicts demand, while for others it underpredicts demand. For the cases where predicted demand is too low, the estimator

FIGURE 2

PERCENTAGE DIFFERENCE: PREDICTED AND ACTUAL FULL-PRICE, LOW-QUALITY TICKET SALES

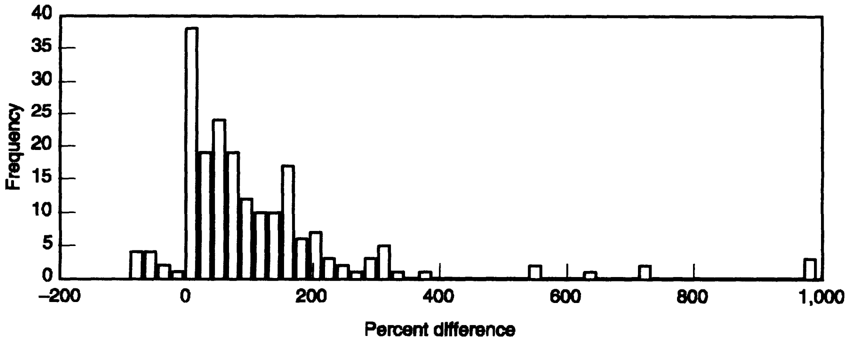
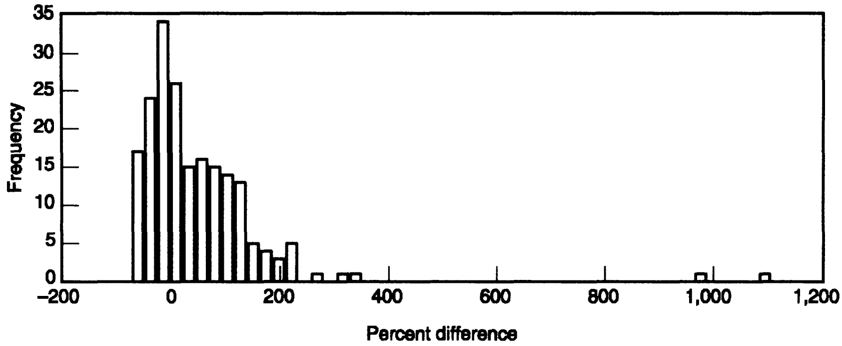


FIGURE 3

PERCENTAGE DIFFERENCE: PREDICTED AND ACTUAL BOOTH TICKET SALES



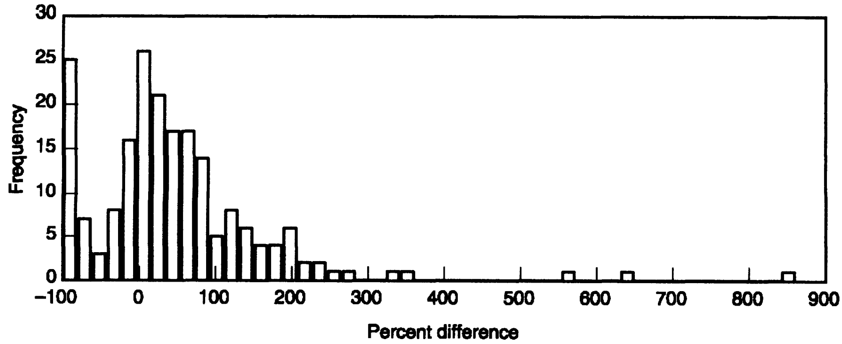
seeks to increase predicted demand, at the potential cost of exacerbating overestimates of demand in other cases. But the capacity constraints serve to limit the magnitude of overestimates of demand. Consequently, the estimator exploits the capacity constraints to limit the overestimates, giving rise to above-average levels of demand for most observations. Some verification of this comes from the result that demand for the low-quality seats is overestimated the most frequently, and this category has the smallest capacity constraint.

Own-price, cross-price, and income elasticities are presented in Table 4. These are obtained by computing predicted market shares under the empirical prices and comparing them to predicted market shares following a 1% increase of the relevant ticket price. The price elasticities are computed with and without capacity constraints.[41] Consider first the capacity-constrained price elasticities. As expected for a monopolist, the own-price elasticities are almost all greater than one. The exception to this is low-quality seats, which is due to poorly predicted low-quality ticket sales reaching the capacity constraint in 182 (out of 199) performances. Actual low-quality ticket sales sell out in only 23 performances. High-quality tickets are the largest revenue category of sales, and the estimate of the own-price elasticity for these tickets is −2.5.

The column on the far right of Table 4 takes into account the fact that booth tickets are always sold at 50% off the price of high-quality tickets. Thus, elasticities in this column are based on 1% increases in both high-quality and booth ticket prices. As expected, this reduces the sensitivity of both high-quality ticket and booth ticket buyers, since there is a diminished incentive to switch

FIGURE 4

PERCENTAGE DIFFERENCE: PREDICTED AND ACTUAL COUPON TICKET SALES



[41] When there are no capacity constraints, a consumers' choice set is not affected by the choices of others ahead in the sequence.

TABLE 4 Demand Elasticities

	Low	Medium	High	Booth	Coupon	High and Booth
Price elasticities with capacity constraints						
Low	−.2468	−.0032	−.0390	.2194	−.1920	.2175
Medium	−.0087	−4.3119	2.8448	5.1226	.4904	7.3497
High	−.0668	.1141	−2.5142	.9310	1.1274	−1.5859
Booth	.1619	.3623	1.3204	−2.8745	.7304	−1.5051
Coupon	−.0320	.0170	.9841	.5510	−1.5202	1.5352
Outside	.0004	−.0000	.0008	.0009	.0014	.0019
Price elasticities without capacity constraints						
Low	−5.4539	0	0	10.5382	3.0179	10.5382
Medium	0	−9.2957	5.9170	6.2060	.0301	12.1230
High	0	.1967	−4.0583	.4150	0	−3.6523
Booth	.1007	2.4070	4.0942	−8.4894	.6894	−4.4629
Coupon	.0036	0	0	.0634	−2.1766	.0634
Outside	.0013	.0085	.0950	.0370	.1129	.1332
Income elasticities with capacity constraints						
Low	.1224		Booth	−.1659		
Medium	.4707		Coupon	−.9125		
High	1.2209		Outside	−.0009		

Notes: Cells for price elasticities are the percentage change in demand for the row product, in response to a 1% increase in the price of the column product(s). The column for "high and booth" is for simultaneous price increases of high-quality, full-price tickets and booth tickets (because booth tickets are always sold at 50% off the price of high-quality, full-price tickets).

from high quality to booth, or from booth to high quality. In addition, the magnitude of the cross-price elasticities on the other categories increases; for example, the elasticity of coupon sales with respect to the high-quality price rises from .98 to 1.53, and with respect to the booth price it rises from .55 to 1.53.

A striking feature of the cross-price elasticities with capacity constraints is that several of them are negative. In the behavioral model, all tickets are substitutes for one another, which ordinarily implies positive cross-price elasticities. The reason for the negative cross-price elasticities is that the capacity constraints cause some consumers to select their second- or lower-ranked alternatives. For example, increasing the price of low-quality tickets causes some individuals to no longer purchase a low-quality ticket, making the ticket available for another individual who may have purchased a medium-quality ticket only because there were no low-quality tickets available previously. In this way, increasing the price of a capacity-constrained category can lead to fewer sales in other categories. To confirm this, I compute price elasticities for the demand system with no capacity constraints, as also reported in Table 4. In this case, all cross-price elasticities are indeed positive.

Table 4 also reports the implied income elasticities for the estimated demand system. Rather than interpret the negative income elasticities on the booth and coupon tickets as evidence of inferiority, we again see the capacity constraints causing substitutions which underlie these income elasticities. Note that the elasticities are computed based on a 1% increase in weekly family income, and that this will translate into a less than 1% increase in each individual's entertainment budget. In any event, high-quality ticket sales appear to be highly sensitive to income, while lower-quality sales are less so.

It was noted at the start of this section that I applied the normalization $\alpha = .01$. As described in Section 3, this variable captures the effectiveness of the coupon technology. To check the robustness of the analysis to this normalization, I reestimate the model with the normalization $\alpha = .02$. The implied price elasticities were all of the same sign, and similar magnitude, to the estimates based on $\alpha = .01$. In the next section I examine a variety of counterfactual experiments and welfare comparisons.

5. Counterfactual experiments and welfare analysis

■ I now describe several counterfactual experiments based upon the estimated demand system. The experiments involve reoptimizing prices under different restrictions, such as uniform pricing, and examining the effect on consumer welfare. No supply-side assumptions were used as part of the demand estimation.[42] However, to perform the experiments in this section I will require a model of how the firm sets prices. I assume the firm chooses prices, $p_t = \{p_{\ell t}, p_{mt}, p_{ht}, p_{bt}, p_{ct}\}$, to maximize expected revenue:

$$R = \sum_{t=1}^{T} \sum_{j \in \Omega \setminus \{o\}} p_{jt} q_{jt}(p_t, \cdot),$$

where $q_{jt} = M_t s_{jt}(p_t, X_t, Z_t, \hat{\theta})$ comes from the estimated demand model ($\hat{\theta}$ denotes the estimated parameters).[43] The following experiments differ in the extent of price flexibility that is allowed—from allowing all prices to vary in every performance, to having all prices equal and constant across all performances and all categories.

By not allowing the firm to choose the quality levels, q_ℓ, q_m, and q_h, the firm side of the model differs from models of second-degree price discrimination in which the firm chooses both qualities and prices. The restriction is motivated by the fact that the producer of a Broadway show rents the theater where the show is performed and makes no physical changes to the auditorium.[44] As with most multiproduct monopoly problems in which the demand for each product is interdependent, it is hopeless to solve for an analytic solution to the firm's optimization problem, except in unrealistically simple cases such as discrete consumer types or a uniform density of consumer types. The problem is further complicated by the stochastic value of the outside alternative.[45] Nevertheless, it is straightforward to solve for optimal prices using numerical methods.

The outcomes from various experiments are compared with a benchmark, and I consider two benchmark cases:

□ **Base-A.** Using the empirical prices, the model provides a prediction of consumer behavior, which yields a measurement of total net utility for all performances. As indicated in Table 5, the measure of total utility in this case is 3.59 (units are meaningless). The associated predicted total revenue is \$6.27 million, and predicted average attendance is 906.9. Due to the discrepancy in predicted attendances from actual attendances, relative comparisons will be the most meaningful. In Table 5, the prices shown for Base-A are the average (across performances) prices in each of the categories.

□ **Base-B.** While Base-A uses empirical prices, Base-B is based on predicted optimal prices. Optimal prices are computed based on restrictions intended to resemble the actual decision making of the firm. Specifically, I assume the firm is constrained to using the same price menu for all performances. Since the actual pricing policy of the firm does not change over time, this assumption is a reasonable approximation for a benchmark scenario. Also, to match the actual behavior of the firm, I assume the booth ticket price is 50% off the full-price, high-quality ticket

[42] Supply-side assumptions can enhance the accuracy of demand-side estimates, but at the risk of introducing misspecification bias.

[43] For simplicity, I assume T is known and fixed.

[44] The problem I analyze is equivalent to the first stage of the nonlinear pricing problem addressed in Rosen and Rosenfield (1997).

[45] See Rochet and Stole (2002) for an analysis of monopoly nonlinear pricing where consumers have random participation constraints.

TABLE 5 **Results of Counterfactual Experiments**

Experiment	Revenue ($ million)	Utility	Average Attendance	p_l	p_m	p_h	p_b	p_c
Actual	4.6951	NA	661.56	16.93	29.20	55.08	27.53	31.01
Base-A	6.2698	3.5859	906.86	16.93	29.20	55.08	27.53	31.01
Base-B	7.8965	3.5775	864.11	23.90	29.80	60.22	30.11	45.26
Uniform	8.0204	3.6039	809.57	50.04	50.04	50.04	NA	NA
No-booth-A	6.7301	3.5837	873.01	16.93	29.20	55.08	NA	31.01
No-booth-B	8.3495	3.5925	873.73	22.28	38.33	51.53	NA	43.23
Booth not 50%	8.4516	3.5900	850.30	24.47	40.86	54.21	38.05	46.32
Nonsticky	8.0194	3.5800	887.37	24.11	30.11	59.73	29.87	46.03

Notes: See Section 5 for explanations of each experiment. The prices shown are the average prices across all performances. For some experiments, prices do not change from performance to performance, for others they do. The figure for average actual attendance does not include wheelchair tickets, standing room, and complimentary tickets. If these categories are included, the average actual attendance is 707.

price ($p_b = .5p_h$).[46] It is necessary to make an assumption about the firm's knowledge of the explanatory variables, X_t and Z_t, and the total number of performances, T. For simplicity, it is assumed the firm has perfect foresight of each of these.

In addition to having a well-specified model of demand, it is important that the firm side of the model also be well specified. A good test of whether the above optimization problem for the firm is a well-specified description of actual behavior is to see if Base-B yields predicted prices that are close to the observed prices.[47] It is worth emphasizing that the estimation procedure in no way "forces" predicted prices to equal observed prices. In this respect, it is a fairly stringent test to expect the estimated demand system, combined with the above model of price-setting behavior, to yield predicted prices that approximate the observed prices. Table 5 shows the predicted optimal prices for Base-B, which should be compared to the top row for actual prices (or, equivalently, the row for Base-A). It is striking how close the predicted prices are to the actual prices. For example, predicted p_h equals $60.22, while the average actual p_h equals $55.08.[48] The coupon price is the least well predicted. Overall, the predicted prices under Base-B provide a degree of confidence that the model is well specified in order to perform the following counterfactuals.

These counterfactuals concern alternative assumptions as to how much flexibility the firm has in determining the price menu. In calculating the welfare effects for consumers, I take into account the utility obtained by those consumers who choose the outside alternative. For some experiments Base-A is the meaningful benchmark, while for others Base-B is the most relevant.

□ **Uniform.** In this experiment the firm is restricted to selling all tickets for all performances at a single price. In particular, there are no booth sales and no coupons. As shown in Table 5, the optimal price in this case is $50.04. Since the experiment involves reoptimizing price, it is most relevant to compare the outcome with Base-B, which also uses optimal prices. Relative to Base-B, attendance drops by 6.3% and utility rises by a trivial amount. Apparently the improvement in utility for people who were paying higher prices before marginally outweighs the loss for people who either pay more or switch to the outside alternative. In addition to these effects there is a new allocation of seat qualities in the theater, which is good for some people and bad for others. The best seats in the house are now more attractive due to the lower price. The worst seats in the house are likely to be filled only by people who have a high taste level for the play.

[46] The service charge imposed by the booth of $2.50 per ticket is also included.

[47] This is actually a joint test of both the demand and supply specifications.

[48] Prototype versions of the demand model gave rise to predicted prices that were higher by several hundred dollars, which I took as compelling evidence of misspecification. Note that predicted prices are based on the estimated coefficients from the demand model. Hence, in principle, it should be possible to determine standard errors for the predicted prices shown in Table 5 (indeed, for all predicted outcomes in Table 5). But as the predicted prices are solved via numerical optimization, computing standard errors for predicted prices is a nontrivial computational task.

A surprising result, however, is that total revenue is higher, albeit by only .6%. How is it that uniform pricing leads to higher revenue than discriminatory pricing? The answer is related to the booth ticket category. In this experiment there is no booth ticket category. When there is one, it could be that a good number of consumers substitute away from buying a full-price ticket toward a booth discount ticket. This substitution effect may be harmful to the firm's profit, especially if the booth discount is restricted to equal 50%. The next three experiments examine this issue more closely.

□ **No-booth-A.** In this experiment the firm uses the empirical prices, with the only modification that no booth tickets are sold. Note that the prices in Table 5 for this experiment are the same as for Base-A. Comparing the results with Base-A, revenue rises by 7.3%, and attendance decreases by 3.7%. The difference in utility is negligible. This provides some confirmation of the argument that selling tickets at the booth is harmful due to the negative effect it has on the demand for full-price tickets.

□ **No-booth-B.** As with the experiment No-Booth-A, there are no tickets sold via a discount booth. In this case, however, the firm reoptimizes the prices of the remaining categories but must apply the same menu in every performance. The useful comparison is with Base-B. Again, revenue rises, this time by 5.7%. Unlike the previous experiment, attendance rises by just over 1%. In effect, the absence of the booth causes the firm to lower the price on the expensive tickets, which has a positive effect on attendance. On the basis of these two experiments, we may conclude that the 50% discount booth tickets are more damaging than beneficial to firm profits. Comparing these results with the uniform pricing experiment reveals that revenue is 4.1% higher under price discrimination (with no booth ticket sales) than with a single price policy. A question remains as to the possible gain of changing the booth discount from 50%, which is addressed in the next experiment.

□ **Booth-not-50%.** In this experiment the firm optimally chooses all ticket prices, including the booth ticket price. In particular, the firm is not restricted to selling booth tickets at 50% off the high-quality price. As with the above experiments, I maintain the restriction that the firm must offer the same menu of prices for all performances. As indicated in Table 5, the firm chooses a higher price for booth tickets. The booth price is now approximately 70% of the high-quality ticket price. Revenue is now 7% higher than in Base-B, and attendance is 1.6% lower. In addition, revenue is also now higher than under uniform pricing, by approximately 5%. Therefore, in principle the booth is an optimal mechanism for selling tickets. A 50% discount appears to be too high from the firm's point of view. For consumers there is also a benefit from raising the price of booth tickets. Since the firm now lowers the high-quality price, the net effect on consumers is not detrimental. Indeed, total utility rises by less than .5%. One may note, however, that the change amounts to a transfer from less wealthy people to wealthy people.

□ **Nonsticky.** A curious feature of behavior in the Broadway theater industry is the presence of sticky prices—firms do not change their pricing policy over time, despite fluctuating demand.[49] While understanding this phenomenon is a research agenda in itself, it is interesting to see how much better off the firm would be in this model if prices could be costlessly adjusted for each performance. In this experiment I return to the restriction that booth tickets are sold at 50% off the price of a high-quality ticket, but I allow the firm to optimally choose the remaining prices on a performance-by-performance basis. The appropriate benchmark is Base-B. The prices shown in Table 5 are the average prices for each of the ticket categories. Surprisingly, revenue increases by only 1.6%, as shown in the table. The increase in revenue from implementing nonsticky prices is less than the gain from altering the booth discount. However, there are reasons to expect that this estimate may either under- or overstate the true impact of nonsticky prices on revenue. On the one hand, if the model allowed for intertemporal substitution by consumers, the revenue gain

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[49] As an aside, more than one Broadway producer claimed to me that prices are not lowered once demand falls for a show because it would send a signal that it is not a good show.

from nonsticky pricing would be even lower. On the other hand, if relative demand for different ticket alternatives is changing over time, the potential increase in revenue from nonsticky prices would be greater than 1.6%.[50] Note also that if there are costs to reoptimizing prices over time, this would reduce the gain to the firm's profit from implementing nonsticky prices.

From these simulations, it appears that the firm stands to gain more by carefully setting a time-invariant price menu than by reoptimizing prices over time. The improvement from nonsticky pricing may be small because the price menu is "robust" to demand fluctuations. In other words, as demand fluctuates, consumers substitute around the price menu instead of going to the outside alternative. For example, when demand shifts down, people shift from buying high-quality, full-price tickets to low-quality, full-price tickets or booth tickets. Of course, costless reoptimization of prices in the face of fluctuating demand should always benefit a firm. But the benefit may be smaller for a firm that offers a menu of prices than for a firm with a single price in each period.

6. Conclusion

■ The data in this study highlight the lengths that a firm can go to in order to sell its product at different prices to different people. By incorporating several kinds of price discrimination into a single framework, designed to represent the example of Broadway theater ticket sales, the theoretical model formalizes how the firm in question is able to sustain such an array of prices. The main results stem from experiments with alternative pricing policies. I find that uniform pricing, relative to the existing price-discrimination policy, implies lower overall attendances for the play without significantly altering the total consumer surplus. This suggests that the apparent lack of concern by antitrust enforcement agencies for price discrimination in final goods may be well founded.

The estimated demand system allows for the calculation of price elasticities for each category of ticket sales. The presence of capacity constraints causes some consumers to buy tickets that would not have been their first choice in the absence of capacity constraints, and it leads to the result that raising the price of one ticket category may cause fewer tickets to be sold in another. Such behavior is apparent from the implied cross-price demand elasticities, some of which are negative for this reason. It seems likely that similar substitution patterns may arise in other industries (such as airlines and hotels) and would be an important factor to be taken into account by the firms in these cases.

The common practice of Broadway producers has been to sell tickets through the TKTS booth at a 50% discount. The counterfactual experiments indicate that the discount booth ticket category draws some consumers away from buying full-price tickets for the show. With a 50% booth discount, it appears that so many consumers substitute away from full-price sales that it would be more profitable to not offer any booth tickets at all. However, if the booth discount were reduced to 30%, there is less substitution away from full-price sales, and the firm can profit from selling tickets at the booth. As a measure of the gain to the firm from price discrimination, based on a 30% booth discount, revenue is approximately 5% higher than under optimal uniform pricing. Alternatively, the firm might offer a 50% booth discount but limit the availability of these tickets to fewer performances, refraining from offering booth tickets in relatively high-demand performances even though the show is not selling out.

The second-degree price-discrimination component of ticket sales for *Seven Guitars* involves only three seat-quality divisions.[51] An obvious question is, why not use more quality divisions than this? There exists significant quality heterogeneity within the high-quality region. An answer to this puzzle may be related to the use of other discount ticket categories.[52] Due to the coupons, there are many more prices paid by consumers than there are seat-quality divisions in the theater.

[50] The model assumes that aggregate demand fluctuates for the show. It is conceivable that the relative demand for different qualities of seating is also changing over time.

[51] In fact, for the majority of performances only two seat-quality regions were used for ticket sales.

[52] Another possible explanation may be the presence of a direct cost for adding further quality divisions. Wilson (1993) shows that the marginal increase in profit from adding more qualities to the price menu is decreasing in the number

It is conceivable that the use of coupons eliminates any gains from adding further seat-quality divisions. It would be interesting to investigate the circumstances under which a firm would prefer to extend one type of price discrimination rather than another.

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of qualities. This suggests that there is a fixed cost incurred in each performance for each additional quality division, which could explain why the producer used three quality divisions in only some performances.