ESSAYS ON DYNAMIC TICKET PRICING: EVIDENCE FROM MAJOR LEAGUE BASEBALL TICKETS

A Dissertation

by

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ABSTRACT

This dissertation includes two essays. In the first essay, I use Major League Baseball ticket data, both in the primary market and in the secondary market, from one anonymous franchise in the 2011 season to study how the franchise can price dynamically to increase its revenue. Compared using a uniform price schedule over time, my model proposes that the franchise can see increased revenue by decreasing ticket prices as the game day approaches. In the counterfactual experiment, the revenue for the franchise can increase by approximately 6.93% as long as the assumption holds that consumers are not strategic in either market. However, if consumers are strategic in purchasing tickets, the revenue for the franchise will increase by around 3.67%.

In the second essay, I focus further on the secondary market using both listing and transaction data from StubHub to study different pricing strategies for the different types of sellers. The data show that the sellers on StubHub can be separated into two types: single sellers and brokers. The single sellers sell tickets in just one or two games during the whole season. The brokers sell many tickets in a given game and also sell tickets in most of the games during the season. I use the data to estimate the probability of sale by the probit model first and then calculate the optimal prices for each listing on each day. The benchmark model shows that brokers price more optimally (meaning smaller expected profit losses) on the final day of sales. However, the two types of sellers have similar expected profit losses on other days.

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1. INTRODUCTION

Professional sports are widely popular in the United States, and because of the convenience of the internet, tickets can now be sold online at any time not only from the official team website, but also from other online marketplaces. This also provides the flexibility of allowing sellers to adjust prices. For instance, in the primary market, the franchise can dynamically price tickets for different games on different days. In the secondary market, like StubHub, the resellers can adjust their listing prices frequently on days leading up to the game. Therefore, the issue of dynamic pricing has become increasingly popular and important in the sports ticket market. In my dissertation, I discuss dynamic pricing issues not only in the primary market for the franchise but also in the secondary market for the different types of resellers.

In the first chapter, I investigate how the franchise can optimally price tickets keeping in mind that resale is quite prevalent in the secondary market. Unlike the hotel and airline industries, to which the sports ticket industry is often compared, the secondary market should be taken into consideration as we discuss the dynamic pricing issue for the franchise in the primary market. In addition, I have considered two types of consumers in the market. Both non-strategic and strategic consumers are introduced to estimate the effect of dynamic pricing.

In the second chapter, I will present how sellers on StubHub use dynamic pricing strategies to optimize their profits on the days leading up to the game. These can be divided into two types of sellers, single sellers and brokers. They are introduced in the market to study how much expected profit loss they have on the different days before the game.

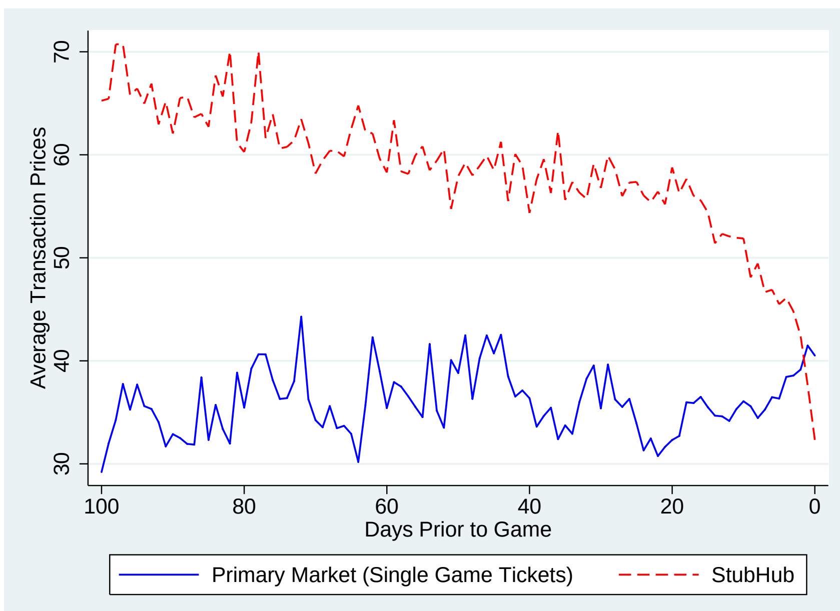
2. EFFECT OF RESALE ON OPTIMAL TICKET PRICING

2.1 Introduction

The franchise can price its tickets differently in three kinds of ways. First, the franchise can set different prices for different seats based on the quality of the seats, so seats with better views are priced higher in the stadium than those with less optimal views. Second, because the demand for each game might not be the same during one season, the franchise can price one particular seat differently for each game. For instance, prices should be higher for some particularly interesting games, and because the demand is higher during the weekend, prices are relatively higher than those on weekdays. Third, besides pricing over different seats and different games, the franchise can also adjust prices during the days before the event. There are two reasons for the franchise to do that. One is that consumers buying tickets on different days might have different willingness to pay, so the franchise can provide different prices for different types of consumers. The other reason is that the demand may fluctuate during the days before the event, so adjusting prices in response to changing demand elasticity may increase the revenue. For example, for those more popular games, the franchise might increase prices over time if the demand increases as the event approaches.

For these three methods, the first two have been widely used for all the franchises, and the third one was first introduced by San Francisco Giants in 2009. Nowadays, more than half of the Major League Baseball franchises have implemented dynamic pricing for their tickets. Because of the existence of the secondary market and the behavior of consumers, it is plausible to understand the benefit of dynamic pricing in the days before the event. In the sports ticket market, the secondary market plays an important role in competition; sellers in the secondary market might change their listed prices to respond to the price changes in the primary market. In addition, the behavior of consumers can determine the effect of dynamic pricing. For instance, the dynamic pricing might not have the effect on the revenue if consumers can predict the future price and strategically choose when to purchase tickets. In this chapter, I consider the behavior of consumers and the competition between the primary and the secondary market to study whether the franchise can dynamically change prices during the days before the event to increase the revenue.

Figure 2.1: Average Prices in Both Markets Over Time



I use Major League Baseball tickets as the example. The data consist of transaction information in the primary market and the secondary market (StubHub) for all the home events of one anonymous Major League Baseball team in the 2011 season. Figure 2.1 shows the price trends in the two markets. StubHub is the most popular secondary market for sports tickets in the United States. Sellers can list their tickets on StubHub anonymously and can easily change listed prices at any time. On StubHub, prices decline over time because sellers have decreasing opportunity cost of holding tickets (Sweeting, 2012). However, in the primary market tickets are sold by the fixed price menu announced in the early season. The fluctuation of prices in the primary market only depends on the quality of seats sold.

Although there is a price difference between the two markets in Figure 2.1, there is almost no difference in the transaction costs of purchasing across the two markets. On the buying pages of the Major League Baseball official website, the link to StubHub can also be found. Consumers can easily go to the StubHub website to search for tickets if they can not find tickets they want available in the primary market. Therefore, I append the two markets together and jointly estimate the demand for both markets. In order to capture the difference between the two markets and to rationalize the price difference for consumers, I include the dummy variable for the secondary market which can be explained as consumers' loyalty to StubHub.

In the demand estimation, two kinds of models are introduced to describe two different kinds of consumers, non-strategic and strategic consumers. Although Sweeting (2012) finds that consumers are not strategic in the secondary market, such as eBay and StubHub, the pricing strategy by franchises can be treated as public information for consumers. Therefore, strategic consumers should also be considered because consumers might choose the optimal time to buy tickets by this public information. In order to estimate the revenue change after dynamic pricing by the franchise, I separately estimate two extreme models: one is the static demand model with all the non-strategic consumers, and the other one is the dynamic demand model with all the strategic consumers. Then, in the real world with two types of consumers mixed together, the revenue change might be within the range of the two extreme cases.

In the static demand model, homogeneous consumers enter into the market randomly to purchase tickets, and they leave the market if they decide not to buy any tickets. I use the random utility discrete choice model to estimate the static demand for the two markets. In the dynamic demand model, consumers are homogeneous and strategic in choosing the time of purchasing tickets. In the beginning, all the consumers come into the market and start to buy tickets in both markets. If they do not buy tickets in the current period, they can stay in the market and wait to buy tickets in the next period. Consumers compare tickets available in the current period with those expected to appear in the future, and they decide not to buy tickets today if they expect to gain higher utility in the future. The model follows the dynamic BLP-style model in Gowrisankaran and Rysman (2012) and Conlon (2012), and I exclude the upgrade choice for consumers in the model. However, in order to mitigate the burden of computation, I assume that consumers are homogeneous and have the same perception of the future, so there is no random coefficient term for prices or other characteristics in the model.

After estimating two kinds of demand systems, I model the behavior of sellers in the secondary market. The intertemporal problem for sellers in the secondary market is to decide the optimal price of tickets based on the current demand and the expected future value. First, I use the true data and estimated price elasticities to recover the expected value of tickets for sellers in each period. Then, in the counterfactual experiment, we can assume the same expected value of tickets for each seller in each period and solve the optimal price in the secondary market when the franchise changes the price in the primary market. Consequently, the counterfactual experiment shows that the franchise can use a declining price schedule instead of uniform price to increase revenue. In the static demand model, revenue can be increased by around 6.93% compared with that in the uniform price. However, the revenue change for the franchise becomes smaller if consumers are assumed strategic in the dynamic model, and the revenue can only be increased by around 3.67%.

This chapter focuses on an important component of a franchise's pricing problem — dynamically pricing single game ticket prices as gameday approaches. A complete analysis of optimal pricing, including the pricing of season tickets, is beyond the scope of this paper. Season ticket pricing can interact with single game pricing in some important ways. For instance, the number of consumers buying season tickets might be affected if the franchise changes the original fixed price menu into the dynamic one. This paper does not consider the effect of season tickets. The direct effect should be the revenue loss from the season ticket. Some resellers might not want to buy season tickets because the expected profits for reselling become lower. In addition, the indirect effect is the distortion of the supply side in the secondary market. Less sellers sell their tickets in the secondary market, so prices might go up because of less competition.

The remainder of this chapter is organized as follows. Section 2.2 reviews the related literature. Section 2.3 summarizes the data in both markets. Section 2.4 presents the model including the demand side and the supply side. Section 2.5 shows the estimation method and results. Section 2.6 provides the counterfactual experiment based on the result of demand estimation. Section 2.7 concludes the research.

2.2 Literature Review

In this section, two groups of literature related to ticket pricing are introduced. First, I mention some literature using price discrimination to describe how the franchise prices tickets in the stadium. Then, some theoretical and empirical literature is presented to discuss the effects of resale in the market.

For ticket pricing in one stadium, Courty (2000) is a good review to discuss several categories of ticket pricing issues in the entertainment market, including the art, music, and sports events. Besides the pricing strategy based on the quality of seats, the most prevalent issue in ticket pricing literature is price discrimination. Theoretical literature discusses price discrimination within different frameworks. Rosen and Rosenfield (1997) use second-degree price discrimination to discuss how the monopoly franchise prices tickets under the deterministic demand. Dana, Jr (1999) shows that the franchise can price differently for the homogeneous seats under the uncertain demand to increase the profits. In the empirical research, Leslie (2004) uses data from Broadway theater to show that observed price discrimination can increase the firm's profit relative to uniform pricing policies. In addition, Courty and Pagliero (2012) find the same effect of price discrimination in the concert tour data.

As the resale becomes prevalent in the market, more literature has discussed the effect of resale on the profits of franchises and the welfare of consumers. Theoretical literature always uses the two-period model to illustrate the role of brokers (see Courty (2003a), Courty (2003b), Geng, Wu, and Whinston (2007), and DeSerpa (1994)). Most literature mentions that resale has a negative effect on franchise profits, and the franchise can not capture the profits earned by brokers. However, Karp and Perloff (2005) propose a different model to sketch the benefits of resale, they find that the franchise may benefit from brokers if the franchise can not distinguish types of consumers.

Furthermore, some empirical literature uses anti-ticket scalping laws to identify the effects of resale. Williams (1994) uses NFL data to find that prices are lower under the anti-ticket scalping law, and the franchise charges higher ticket prices if resale is prevalent in the market. Elfenbein (2006) finds that ticket resale regulations do affect online trading. Because regulations reduce the number of transactions online, prices in the secondary market become higher. Depken (2006) indicates that franchises can increase revenue by the anti-scalping laws as the attendance is not affected by the law. Besides using the anti-scalping laws to identify the effect of resale, Leslie and Sorensen (2014) use the structural model to show that resale does increase allocative efficiency. The data they use are market sales in the primary and secondary market for a sample of rock concerts, and the two-stage model allows consumers to buy in the first stage and to resell in the second stage. As a result, the welfare of consumers attending the event may decrease because of resale, and the surplus generated by efficient reallocation is gained mostly by resellers.

To analyze sports tickets in the secondary market, Sweeting (2012) uses Major League Baseball ticket data from two online secondary markets: eBay and StubHub. He finds that prices are decreasing over time as the game date approaches, and the sellers lower the price because of the decreasing opportunity cost of holding tickets. Furthermore, he uses data to test how accurately traditional dynamic pricing models describe sellers' behavior, and he shows that simplest dynamic pricing models can fit the behavior of sellers very well, and consumers are not strategic in buying tickets in the secondary market.

Unlike the previous literature which nests the primary market and secondary market together as two separate periods, I put these two markets together in each period. The advantage of putting two markets together is that we can understand how consumers choose between two markets, and the competition between markets can be captured by the model. However, the drawback is that consumers buying tickets in the primary market are not allowed to resell their tickets in the secondary market. Although it sounds unreasonable in the real world, the data shows that most resellers buy their tickets from the primary market by season ticket price and list their tickets much earlier on StubHub. If we focus on two weeks before the event, not too many consumers actually buy tickets in the primary market and resell those tickets on StubHub. Instead of using the previous literature model to analyze the sports ticket market, I focus more on the competition between the two markets, and the response of resellers is also included into the model.

2.3 Data

2.3.1 Transaction Data

The data contain all the transaction information in both the primary market and the secondary market for all the home events of one anonymous Major League Baseball franchise in 2011.[1] The primary market includes all the channels through the franchise, such as phone, internet, and box office. The secondary market data are only from StubHub, the largest ticket marketplace in the United States.

Table 2.1: Number of Tickets Sold Over Time in the Two Markets

	Primary Market		StubHub
Days Prior to Game	Single Game Tickets	Package Tickets	
0	80,561	0	50,467
1-13	110,087	264	176,455
14-30	123,205	1,032	54,672
31-60	100,606	8,806	44,564
61-100	86,284	39,205	29,014
101-200	193,410	834,253	25,255
201+	3,967	1,150,982	1,147
Total	698,120	2,034,542	381,574

[1] Because of the non-disclosure agreement, I can not reveal any information about the name of the franchise.

In the primary market, based on the method of selling, tickets can be roughly separated as three types: single game tickets, package tickets, and group tickets. Table 2.1 shows the number of tickets sold in the two markets and only presents the number of single game tickets and package tickets for the primary market.[2] As indicated in Table 2.1, over 50 percent of package tickets are sold early in the season, about over 200 days before the game. However, on StubHub, over 50 percent of the transactions happen within two weeks before the event. Therefore, I focus on the data within 13 days prior to the event, and in the primary market only single game tickets are included in the sample.

Furthermore, tickets sold on the last day (0 days prior to the game) are also excluded for two reasons. First, the last day (0 days prior to the game) has different lengths of time for different games because not all the games start at the same time during a day. For those games starting from noon, the number of transactions is much smaller than those starting from evening. Second, the instrumental variable I mention in section 2.5.1 has some problems on the last day.[3] As a result, I only use the sample in 1-13 days prior to the game to estimate the demand and do the rest of analysis.

Besides the selection of the days before the game, I exclude some tickets in some special areas or without seats because it is difficult to compare those seats with most of the tickets in the field. Tickets for the home opener are also excluded because prices are significantly higher than those in any other games. Even though all the data are transaction data, extreme high price tickets might bias the aggregate data. Thus I drop those tickets with prices greater than or equal to three times the face

[2]Adding with the number of group tickets that I see in the data will yield a number very close to the team's attendance; however, to avoid revealing the team's attendance, I only list the number of single game tickets and package tickets in Table 2.1.

[3]See section 2.3.2.

value.

Table 2.2 shows the summary statistics for the full sample and the sample for estimation, including prices, days prior to the game, face values, and characteristics in both markets. In the full sample, the mean price on StubHub is \$47.76, higher than \$34.24 in the primary market. For price dispersion, prices vary not only based on the quality of tickets in the both markets but also across different purchasing time in the secondary market, so the standard deviation on StubHub is \$32.63, greater than \$17.92 in the primary market. Furthermore, the face value indicates the price menu reported by the franchise in the beginning of season, but because the franchise may change the price menu for some particular games or sections during the season, the mean price is higher than the mean face value in the primary market. On StubHub, the difference between the transaction price and the face value can be treated as the markup for sellers on StubHub, and average markup is around \$12.61. Moreover, face value and distance from the seat to home plate can also represent the quality of tickets, so the quality of tickets in the full sample is very similar in the two markets. In addition, the front row of section dummy shows that tickets sold on StubHub have more front row seats (9.5 percent of tickets sold), compared with those single game tickets sold in the primary market.

If we focus on the sample in 1-13 days prior to the game, exclude those transactions with extreme high prices, drop those tickets in some special areas, and exclude the data from the home opener, the summary statistics are shown in the bottom part of Table 2.2. The average number of transactions in the primary market is 729.26 per game, less than 1589.09 on StubHub. Consumers tend to buy tickets from the secondary market within two weeks before the game. Furthermore, based on the face value and the distance from the seat to home plate, the quality of tickets on StubHub is worse than that in the primary market. Although the percentage of front row seats

Table 2.2: Summary Statistics

	Obs.	Mean	Standard Deviation	Max	Min
Full Sample					
Primary Market					
Price ($ per seat)	540,596	34.242	17.920	108	1
Days prior to game	540,596	65.081	57.382	245	0
Face value ($ per seat)	540,596	33.743	17.209	95	12
Distance from seat to home plate	540,596	277.786	95.043	439.3	82.62
Front row of section dummy	510,867	0.029	0.167	1	0
StubHub					
Price ($ per seat)	345,207	47.758	32.628	706	0.01
Days prior to game	345,207	26.795	39.562	303	0
Face value ($ per seat)	345,207	35.150	18.977	95	12
Distance from seat to home plate	345,207	271.941	93.725	439.3	72.81
Front row of section dummy	342,236	0.095	0.293	1	0
Sample for Estimation					
Primary Market					
Price ($ per seat)	58,341	40.131	18.407	108	10
Days prior to game	58,341	6.148	3.943	13	1
Face value ($ per seat)	58,341	37.788	16.828	76	12
Distance from seat to home plate	58,341	250.638	89.389	424.2	129.9
Front row of section dummy	54,423	0.007	0.083	1	0
StubHub					
Price ($ per seat)	127,127	39.684	22.692	225	0.01
Days prior to game	127,127	4.735	3.544	13	1
Face value ($ per seat)	127,127	33.673	17.051	76	12
Distance from seat to home plate	127,127	279.241	90.776	424.2	129.9
Front row of section dummy	126,610	0.073	0.260	1	0

is higher on StubHub, tickets sold in the secondary market are distributed amongst the areas with lower face values. In addition, prices in the secondary market still vary more than those in the primary market because of the descending price trend on StubHub. The maximum transaction price on StubHub is $225, and the minimum one is only $0.01.

In order to reduce the categories of tickets, I group some sections and define 7 areas as Figure 2.2 shows. On the infield side, areas 1, 2, and 3 are on the first floor, and areas 5 and 6 are on the second floor. On the outfield side, tickets are grouped by each floor, named as area 4 and area 7. Tickets in the same area can be treated as homogeneous goods.

Because the demand for each area is different in the secondary market, price patterns on StubHub vary across areas. Figure 2.3 shows the price patterns in the two markets for areas 1, 3, 5, and 7, and the dotted lines represent 95 percent confidence intervals. For all areas, prices are decreasing over time in the secondary market, as the evidence found in Sweeting (2012). Although the declining prices on StubHub in Figure 2.1 can also be explained as the composition of the tickets sold, Figure 2.3 clearly indicates that the prices in the secondary market is still declining over time even though we control the quality of tickets.

In areas 1 and 5, Figure 2.3 shows that the price on StubHub is only lower than that in the primary market when the event approaches. In order to sell tickets out on StubHub, sellers might lower the price dramatically in the last few days before the game. In area 3, the descending prices are significantly higher than those in the primary market except the last day. In the last day, prices in the two markets are almost the same. In area 7, the descending prices on StubHub are higher than prices in the primary market at any time, which might implies that the franchise underprice this area, or some consumers have some reasons to choose a higher price

Figure 2.2: Area Location in the Baseball Field

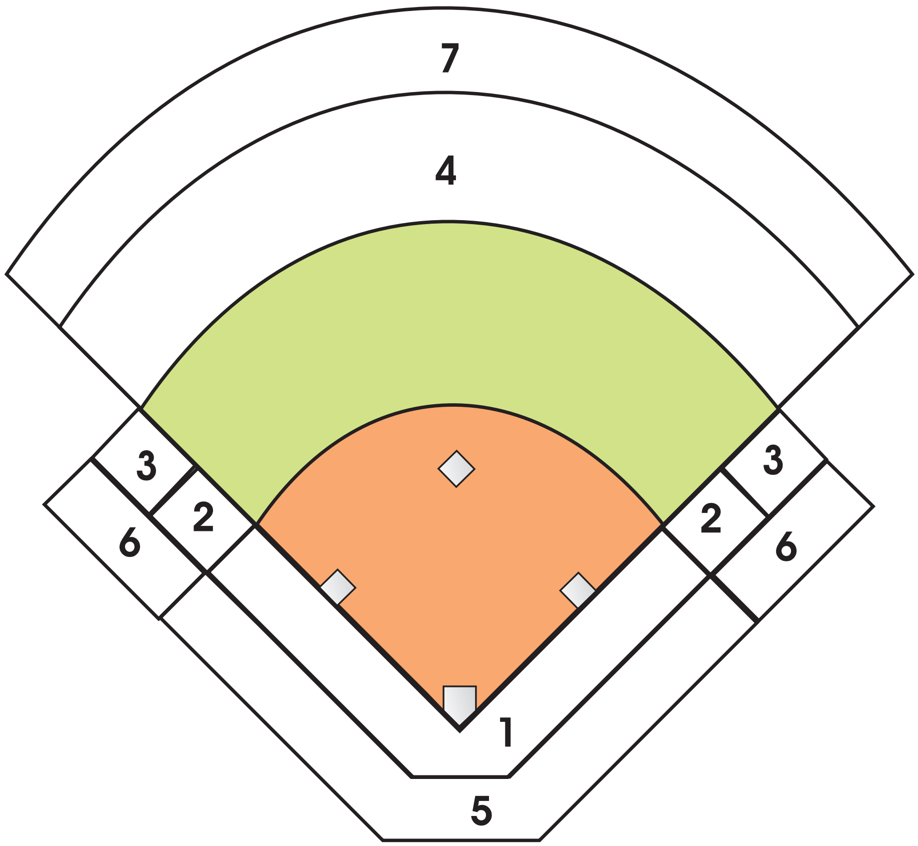
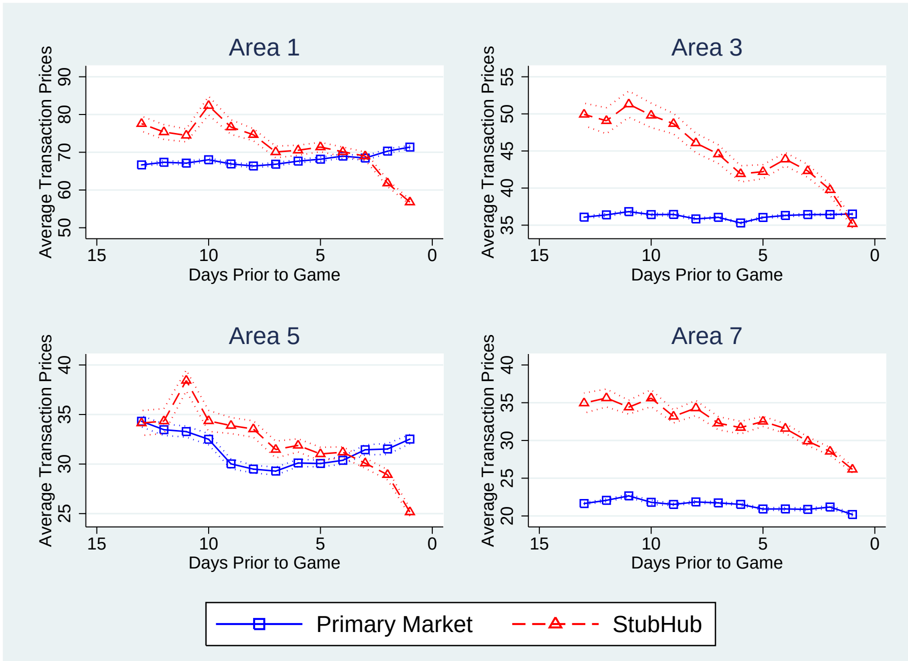


Figure 2.3: Prices for Different Areas in the Two Markets Over Time



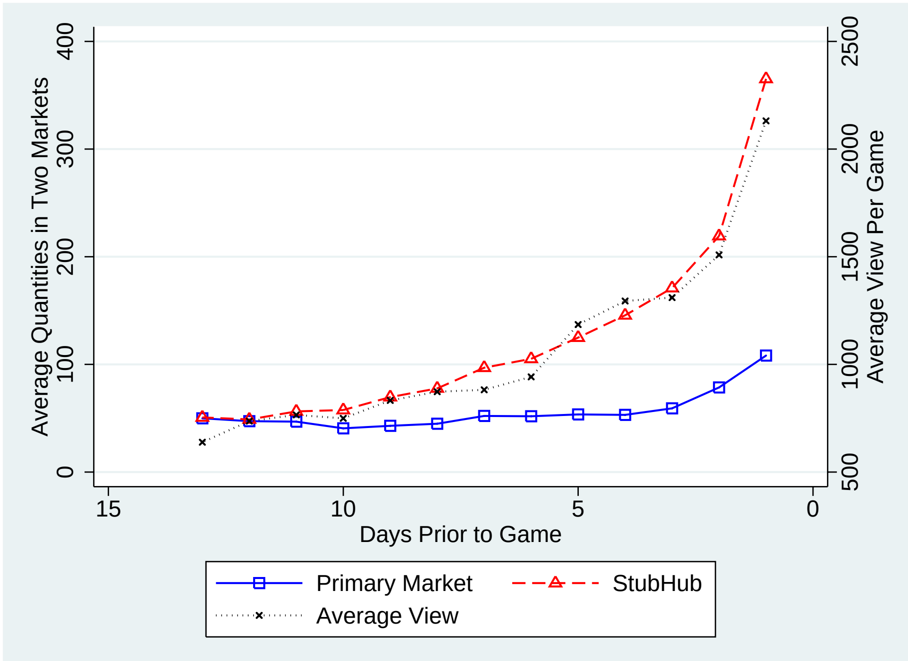
on StubHub.

To estimate the demand in the two markets, I aggregate the data by area, by market, by day prior to the game, and by game. For each game, the aggregate data contain the average prices, quantities, and other average characteristics for 7 areas over 13 periods. For those spots without the transaction data, tickets are assumed unavailable at that time.

2.3.2 Other Data

Besides the transaction data, I use website viewing data to approximate the number of consumers in the market at a given point in time. This data contain the number of website hits on the franchise pricing pages for each game everyday. Figure 2.4 shows the number of view increases as the gameday approaches. In 10 days prior to the game, the average view per game is only 800, but it dramatically increases to

Figure 2.4: Average View and Quantity in Both Markets Over Time



over 2000 on the last day before the game. Furthermore, in Figure 2.4, the average transaction quantity per game increases over time in both markets because of the increase in potential consumers, but the number of tickets sold in the primary market is not as proportional as the number of potential consumers.

In addition, I collect the listing data on StubHub every day from March 25, 2011 to September 28, 2011. The data include the seat information on the buying page, such as price, quantity, row number, and seat number. However, the StubHub transaction data do not contain the information about seat number. The only way to connect the StubHub transaction data with the primary market transaction data is through the listing data. In this way, the primary market buyer information can be used to identify the seller's information on StubHub. Then, we can get the information about seller's cost shock to be the instrumental variable (See section

2.5.1). Unfortunately, the listing data is not perfect on the day of the event[4], so I can not get the seller's complete information for 0 days prior to the game.

2.4 Model

The model includes three parts: the demand side in the two markets, the supply side in the secondary market, and the franchise profits maximization problem. In addition, two models are presented for the demand side. One is the static demand model where consumers can enter the market on a given day before the game, choose to purchase or not, and then exit the market. The other one is the dynamic demand model which specifies strategic consumers choosing the optimal time for purchasing tickets.

2.4.1 Static Demand Model

The model follows the random utility discrete choice model. For a given game g, there are T periods, indexed by $t = \{1, 2, ..., T\}$. Consumers start to buy tickets from the first period $t = 1$, and the game starts after the last period $t = T$. Consumers are assumed to have only one unit demand, and they come into the market randomly in some period. In each period, they can choose one of the available tickets in the market or decide not to buy anything. Once they decide not to buy any tickets, they leave the market forever. In the model, the market contains the primary market and the secondary market. Consumers do not have any search cost inside the market, they can observe all the available tickets and easily compare their prices. Furthermore, consumers are assumed to attend the event for sure, so they do not resell their tickets in the market.

In order to simplify the notation, I only specify the setting for one game g and drop the subscript g. There is a set of areas $j = 1, 2, ...J_t$ available at each period t.

[4] From August 2011, the listing data are not collected on the day of the event.

For each area j, characteristic $\mathbf{x}_{jt}$ and price p_{jt} are different in each period t. Here, $\mathbf{x}_{jt}$ contains the observed characteristics, such as dummies for floor level and the average distance between available seats and home plate. If a consumer i buys the ticket in area j at period t, then she gains the utility

$$u_{ijt} = \gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + \mathbf{D}_t\boldsymbol{\gamma}_2 + \xi_{jt} + \epsilon_{ijt}, \tag{2.1}$$

where D_t are a set of dummies to specify the purchasing time, ξ_{jt} is unobserved demand shock, and ϵ_{ijt} is an idiosyncratic taste for consumers. Because consumers buying tickets in the same area might have various utilities depending on the time of purchasing, the period dummies are included to control the mean utility for different period consumers. However, the period dummies only affect the purchase of the outside good and do not affect their decision to choose the area. Unobserved demand shocks ξ_{jt}, such as injury news of players, is only observed by consumers. Idiosyncratic taste ϵ_{ijt} is distributed i.i.d. across time, areas, and individuals according to a Type I extreme value distribution.

Define the mean utility of buying the ticket in area j at period t as $v_{jt} = \gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + D_t\boldsymbol{\gamma}_2 + \xi_{jt}$. By integration of the idiosyncratic error term, the market share of area j at period t is

$$s_{jt} = \frac{\exp\{v_{jt}\}}{1 + \sum_{k=1}^{J_t} \exp\{v_{kt}\}}. \tag{2.2}$$

Furthermore, the option of outside goods is defined as $j = 0$, which means consumers do not buy any tickets and leave the market. After the mean utility of buying nothing is normalized as 0, then the market share of outside goods is

$$s_{0t} = \frac{1}{1 + \sum_{k=1}^{J_t} \exp\{v_{kt}\}}. \tag{2.3}$$

From equation (2.2) and (2.3), the estimating equation for demand can be written as:

$$\ln(s_{jt}) - \ln(s_{0t}) = v_{jt} = \gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + \mathbf{D}_t\boldsymbol{\gamma}_2 + \xi_{jt}. \tag{2.4}$$

The market share of area j and the market share of outside goods can be observed from the data; hence, the mean utility v_{jt} can be calculated directly in the static demand model.

2.4.2 Dynamic Demand Model

In the dynamic demand model, the only difference from the static demand model is that consumers who do not buy a ticket in the period $t < T$ can stay in the market and make the decision again in the next period $t + 1$. The outside good option becomes the expectation of future purchasing.

Let $\epsilon_{it} = (\epsilon_{i0t}, \epsilon_{i1t}, ...\epsilon_{iJ_tt})$ be the idiosyncratic taste for consumer i at period t for all the areas. The decision for consumer i at time t only depends on the taste ϵ_{it} and the mean utility of currently available areas $\{v_{jt}\}_{j=1}^{J_t}$, and the expectation of future available tickets depends on current available information. Let Ω_t be a state variable which contains all the information related to consumer's decision. Then the Bellman equation can be written as

$$V_i(\epsilon_{it}, \Omega_t) = \max\left\{\epsilon_{i0t} + \beta E[V_i(\epsilon_{it+1}, \Omega_{t+1})|\Omega_t], \max_{j=1,\ldots,J_t}\{v_{jt} + \epsilon_{ijt}\}\right\}, \tag{2.5}$$

where $V_i(\epsilon_{it}, \Omega_t)$ is the value function for consumer i at period t and β is the discount factor for the future. Equation (2.5) indicates that the current value of the consumer is to maximize the value between waiting to the next period and choosing the favorite ticket from the available choice set.

Define the logit inclusive value as

$$\delta_t = \ln\Big(\sum_{j=1}^{J_t} \exp\{v_{jt}\}\Big). \tag{2.6}$$

The logit inclusive value captures the value of ex-ante purchasing tickets in the market. By the assumption of Type I extreme value distribution error term, the value function can be integrated as:

$$\mathrm{EV}(\Omega_t) = \ln\Bigg(\exp\Big(\beta E[\mathrm{EV}(\Omega_{t+1})|\Omega_t]\Big) + \exp(\delta_t)\Bigg), \tag{2.7}$$

where $\mathrm{EV}(\Omega_t) = \int_{\epsilon_{it}} V(\epsilon_{it}, \Omega_t)$ means the expectation of value function over ϵ_{it}. Following the previous literature (see Gowrisankaran and Rysman (2012), Melnikov (2013), and Conlon (2012)), we can assume that inclusive value is sufficient for consumers to make the decision, which means $EV(\Omega_t) = EV(\delta_t)$ and $\mathrm{Prob}(\Omega_{t+1}|\Omega_t) = \mathrm{Prob}(\delta_{t+1}|\delta_t)$. Intuitively, the inclusive value represents the situation in the market including the number of available areas, ticket prices, and ticket characteristics which directly affect the utility; therefore, consumers only track the inclusive value to predict the future value. One of the possible disadvantages is that prices and characteristics might affect the inclusive value in different ways over time. As the game day approaches, decreasing prices make the inclusive value become higher, but fewer available tickets or worse ticket quality might cause the inclusive value to become less. To model how consumers predict the future states, I simply assume that consumers use the current state to predict the next state:

$$\delta_{t+1} = \pi_0 + \pi_1 \delta_t + \eta_t. \tag{2.8}$$

Then the market share of area j at period t is

$$s_{jt} = \frac{\exp\{v_{jt}\}}{\exp\big\{\beta E[\mathrm{EV}(\delta_{t+1})|\delta_t]\big\} + \sum_{k=1}^{J_t} \exp\{v_{kt}\}}. \tag{2.9}$$

The value function, equation (2.7), can also be written as:

$$\mathrm{EV}(\delta_t) = \ln\left(\exp\Big(\beta E[\mathrm{EV}(\delta_{t+1})|\delta_t]\Big) + \exp(\delta_t)\right). \tag{2.10}$$

Define $\mathbf{v}$ is the vector containing all the mean value $\{\{v_{jt}\}_{j=1}^{J_t}\}_{t=1}^{T}$. Then we need two loops to obtain the mean utility vector $\mathbf{v}$. The outside loop is the contraction mapping based on Berry, Levinsohn, and Pakes (1995) and Gowrisankaran and Rysman (2012):

$$v_{jt}^{\text{new}} = v_{jt}^{\text{old}} + \psi\Big(\ln\left(\bar{s}_{jt}\right) - \ln\left(\hat{\bar{s}}_{jt}(\mathbf{v}^{\text{old}})\right)\Big), \quad \forall\, j, t, \tag{2.11}$$

where $\bar{s}_{jt}$ is the observed market share from the data, $\hat{\bar{s}}_{jt}$ is the market share predicted by the model, and ψ is generally set as $1-\beta$. Given any value of mean utility $\mathbf{v}$, we can obtain the true mean utility $\mathbf{v}$ by the iteration of equation (2.11).

To predict the market share by the mean value vector $\mathbf{v}$, we need the inner loop for the value function. Given the mean value vector $\mathbf{v}$, the logit inclusive value δ_t can be calculated by equation (2.6) in each period t. Also, $\hat{\pi}_0$ and $\hat{\pi}_1$ can be estimated by equation (2.8). Then I discretize δ_t into 50 grid points.[5] Based on $\hat{\pi}_0$ and $\hat{\pi}_1$,

[5]The range for δ_t is from $\min(\delta_t) - 0.2(\max(\delta_t) - \min(\delta_t))$ to $\max(\delta_t) + 0.2(\max(\delta_t) - \min(\delta_t))$.

the transition matrix can be obtained for each state. Given the initial guess of the value function $\text{EV}(\delta_t)$, the new value function is iterated by equation (2.10). Once we have the true value function for each state, the market share can be predicted by equation (2.9).

Then we can have the estimated equation as

$$v_{jt} = \gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + \mathbf{D}_t\boldsymbol{\gamma}_2 + \xi_{jt}, \tag{2.12}$$

where v_{jt} is solved by two iteration loops. Because I assume that consumers are homogeneous, the random coefficient term is not in the model. Therefore, I do not need to nest these two iterations into the estimation, and the mean utility can be obtained independently. To estimate equation (2.4) and (2.12), I use the Generalized Method of Moment (GMM) to deal with the endogeneity problem. (See section 2.5)

2.4.3 Supply in the Secondary Market

On the supply side, there are many sellers in the secondary market. Sellers can price dynamically over time to maximize their profits, and different kinds of sellers might have different strategies of pricing. In order to simplify the problem, I follow the theoretical model in Sweeting (2012) but assume that sellers in the same area are homogeneous.

To omit the notation for different games, I sketch the seller problem for a given game g. Assume in the area j at period t, there are M_{jt} homogeneous sellers in this area, and there are N_t buyers in the market. The number of buyers and sellers are assumed exogenous. In the static demand case, there is no problem to treat the number of new coming consumers as exogenous because consumers should leave the market after the end of period. However, when consumers are strategic, we can not separately identify the waiting consumers and new coming consumers. The only possible method is to treat either the number of new coming consumers or the number of total consumers as exogenous. Here, the easier way is to assume the number of total consumers is N_t.

In addition, after each period t sellers have the expected value for their tickets, denoted as EV_{jt+1}. In the last period $t = T$, it can be interpreted as the scrap value of the ticket. For instance, if the seller can not sell the ticket in the last period, she still can attend the event directly and gain the value. In the period $t < T$, sellers can have many options. She can either continue selling the ticket or decide not to sell the ticket on StubHub. Of course, she can also decide to sell in other secondary markets. Therefore, the expected value after the period t is not necessarily equal to the value of the maximization problem in the beginning of the period $t + 1$. The seller's problem can be separated period by period, and the seller decides the price in the beginning of each period t to maximize the expected profits which includes both the possible revenue in period t and the expected value after period t. Each seller can only have one ticket, so the problem for seller k in area j can be written as

$$\max_{p_{kt}} p_{kt}\Phi_{kt}(p_{kt}, p_{-kt}) + (1 - \Phi_{kt}(p_{kt}, p_{-kt}))EV_{kt+1}, \tag{2.13}$$

where $\Phi_{kt}(p_{kt}, p_{-kt})$ is the probability of sale and p_{-kt} are all other prices by other sellers in the market. Because all the sellers on StubHub are small relative to the market, they are unlikely to have the market power. The function $\Phi_{kt}(.)$ is assumed not affected by any single seller.

If the seller k sets a higher price than the price level in area j, which is $p_{kt} > p_{jt}$, then the probability of sale is $\Phi_{kt} = 0$. However, if $p_{kt} = p_{jt}$ for all seller k in area j, then the probability of sale is $\Phi_{kt} = \frac{s_{jt}(p_{kt}, p_{-kt})N_t}{M_{jt}}$. The first order condition is:

$$\Phi_{kt}(p_{kt}, p_{-kt}) + \frac{\partial \Phi_{kt}(p_{kt}, p_{-kt})}{\partial p_{kt}}(p_{kt} - EV_{kt+1}) = 0. \tag{2.14}$$

Based on the first order condition, each seller can choose the optimal price p^*_{kt}:

$$p^*_{kt} = EV_{kt+1} + \frac{\Phi_{kt}(p^*_{kt}, p^*_{-kt})}{\left|\frac{\partial \Phi_{kt}(p^*_{kt}, p^*_{-kt})}{\partial p_{kt}}\right|}. \tag{2.15}$$

Because sellers in area j are homogeneous, the optimal prices should be the same in area j, which is $p^*_{kt} = p^*_{jt}$ for all seller k in area j. The probability of sale should be $\Phi_{kt} = \frac{s_{jt}(p_{jt}, p_{-jt})N_t}{M_{jt}} \equiv \Phi_{jt}$ because every seller in the same area equally share the same probability of sale. The marginal probability of sale $\frac{\partial \Phi_{kt}}{\partial p_{kt}}$ can be assumed equal to $\frac{\partial \Phi_{jt}}{\partial p_{jt}}$ if all the sellers in the same area can expect to change the price simultaneously. Therefore, all the first order conditions at period t can be reduced as J_t first order conditions only for different areas:

$$p^*_{jt} = EV_{jt+1} + \frac{s_{jt}(p^*_{jt}, p^*_{-jt})}{\left|\frac{\partial sjt(p^*_{jt}, p^*_{-jt})}{\partial p_{jt}}\right|} \quad \forall\ j = 1, 2, ...J_t, \tag{2.16}$$

where $s_{jt}(p^*_{jt}, p^*_{-jt})$ is the equilibrium market share of area j at period t, and p_{-jt} are prices for other areas. Intuitively, the price for area j at period t only depends on the expected value EV_{jt+1} and the elasticity in the market. Empirically we can recover the seller's expected value after using the data to calculate the elasticity of demand.

2.4.4 Franchise Problem

In this section, I focus on the revenue from single-game tickets. Theoretically the franchise can set the prices for all of the areas and periods in the primary market, denoted as $\left\{\{p_{jt}\}_{j\in\mathcal{J}_{0t}}\right\}_{t=1}^{T}$, where $\mathcal{J}_{0t} = \{\ j \mid \forall j$ in the primary market at time $t\}$. In the real world the franchise does not price dynamically over time, $\left\{\{p_{jt}\}_{j\in\mathcal{J}_{0t}}\right\}_{t=1}^{T} = \{p_j\}_{j\in\mathcal{J}_0}\ \forall t$, where $\mathcal{J}_0 = \{\ j \mid \forall j$ in the primary market$\}$. The revenue under the original price menu $\{p_j\}_{j\in\mathcal{J}_0}$ should be

$$\sum_{t=1}^{T}\sum_{j\in\mathcal{J}_0} N_t s_{jt}(p_{jt}, p_{-jt})p_{jt}. \tag{2.17}$$

If the franchise can change the price without any cost, the maximization problem for the franchise is

$$\max_{\{\{p_{jt}\}_{j\in\mathcal{J}_{0t}}\}_{t=1}^{T}} \sum_{t=1}^{T}\sum_{j\in\mathcal{J}_{0t}} N_t s_{jt}(p_{jt}, p_{-jt})p_{jt}. \tag{2.18}$$

We ignore the capacity constraint for the franchise because in the data tickets are always available in all areas in the primary market. However, it is difficult to solve this maximization problem. In the counterfactual experiment in section 2.6, I use a new price menu to calculate the revenue and compare that with the original one.

2.5 Estimation and Results

2.5.1 Endogeneity Problem

The demand can be estimated by equation (2.4) and (2.12), but the unobserved demand shock ξ_{jt} might be correlated with the price p_{jt} in some case. In the primary market, the price variation primarily depends on the quality of seats and the opponents of games. For instance, facing a popular opponent, the franchise can expect a higher demand and set a higher price. Once we control the location of the seat and the information of the game, the unobserved demand shock ξ_{jt} should not correlate with the price because the price is always set by the franchise in the beginning of the season. However, in the secondary market, equilibrium price correlates with the unobserved demand shock ξ_{jt} even though we have already controlled for seat quality and opponent characteristics. For instance, some news about a player before the game might change the demand and the equilibrium price.

In the previous literature, it is common to use cost shifters to identify the demand. Here, I use the proportion of sellers buying tickets in the primary market by package prices as the instrumental variable for the demand in the secondary market. The instrumental variable varies primarily across different areas and different games but does not vary substantially over time. From the data, those sellers buying tickets by package prices do price lower because they have lower opportunity cost than others. They have already used the cheaper price to buy tickets in the primary market. Also, they can bear the loss in the following games if they have already sold tickets for some popular games in higher prices. As a result, for those areas with higher proportion of sellers holding package tickets, the average transaction price is also lower.

The exclusion restriction of this instrumental variable strategy is that there is no correlation between the cost shifter and the unobserved demand shock. For those package buyers in the primary market, they always buy tickets at the beginning of the season. The exclusion restriction would be called into question if sellers decide to resell their tickets based on the information of the unobserved demand shock. From the data I can observe, sellers almost always list their tickets very early in the season on StubHub. Thus, the proportion of sellers as package buyers in the primary market could be the potential instrumental variable to identify the demand.

2.5.2 Demand Estimation Results

After the mean utility v_{jt} is recovered by the observed market share, the unobserved demand shock $\xi_{jt} = v_{jt} - (\gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + D_t\boldsymbol{\gamma}_2)$ can be written as

$\xi_{jt}(\alpha, \boldsymbol{\gamma})$, where $\boldsymbol{\gamma} = (\gamma_0, \boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2)'$. Define $\boldsymbol{\xi}_0(\alpha, \boldsymbol{\gamma})$ as a vector containing all the unobserved demand shock in the primary market $\left\{\{\xi_{jt}(\alpha, \boldsymbol{\gamma})\}_{j \in \mathcal{J}_{0t}}\right\}_{t=1}^{T}$ and $\boldsymbol{\xi}_1(\alpha, \boldsymbol{\gamma})$ as a vector containing all the unobserved demand shock in the secondary market $\left\{\{\xi_{jt}(\alpha, \boldsymbol{\gamma})\}_{j \in \mathcal{J}_{1t}}\right\}_{t=1}^{T}$, where $\mathcal{J}_{1t} = \{\ j \mid \forall j \text{ on StubHub at time } t\}$. Furthermore, define $\mathbf{z}_0$ as a matrix containing all the exogeneous variables in the primary market and $\mathbf{z}_1$ as a matrix containing the instrumental variable and other exogeneous variables in the secondary market. The sample moment condition is

$$\mathbf{m}(\alpha, \boldsymbol{\gamma}) = \begin{bmatrix} \frac{1}{n_0}\mathbf{z}_0'\boldsymbol{\xi}_0(\alpha, \boldsymbol{\gamma}) \\ \frac{1}{n_1}\mathbf{z}_1'\boldsymbol{\xi}_1(\alpha, \boldsymbol{\gamma}) \end{bmatrix}, \tag{2.19}$$

where n_0 and n_1 are the number of observations in the primary market and in the secondary market. Then the GMM estimator is

$$\left(\hat{\alpha}, \hat{\boldsymbol{\gamma}}\right) = \arg\min_{\alpha, \boldsymbol{\gamma}} \mathbf{m}(\alpha, \boldsymbol{\gamma})' W \mathbf{m}(\alpha, \boldsymbol{\gamma}), \tag{2.20}$$

where W is a weighting matrix.

The estimated parameters are shown in Table 2.3. The first column contains the parameter estimates and standard errors from the static demand model, and the last two columns provide the results of the dynamic demand model. The difference between the last two columns is whether dummies for days prior to the game are included in the model or not. In the static demand model, there are two reasons to include dummies for different days. First, consumers coming into the market on different days might have different mean utilities of buying tickets. Second, dummies for different days can be used to control the demand change over time. However, in the dynamic model, consumers are assumed to enter the market in the early beginning, and the waiting behavior of consumers is sketched by the model. There

Table 2.3: Demand Estimates

	Static Model	Dynamic Model	
	(1)	(2)	(3)
Seat quality			
Price ($)	-0.011	-0.074	-0.078
	[0.001]**	[0.013]**	[0.014]**
Distance from seat to home plate (ft)	-0.001	-0.008	-0.008
	[0.000]**	[0.002]**	[0.002]**
First floor dummy	0.193	1.488	1.558
relative to the second floor	[0.031]**	[0.283]**	[0.287]**
Game Information			
Against divisional opponent	0.098	1.916	1.923
	[0.020]**	[0.206]**	[0.206]**
Against league opponent	-0.128	-1.187	-1.178
	[0.029]**	[0.256]**	[0.256]**
Relative to weekday game			
Saturday game	-0.405	-7.878	-7.881
	[0.029]**	[0.221]**	[0.222]**
Sunday game	-0.227	-2.796	-2.796
	[0.025]**	[0.203]**	[0.203]**
Secondary market dummy	0.462	0.261	0.274
relative to the primary market	[0.020]**	[0.177]	[0.177]
Include dummies for	Yes	Yes	No
days prior to game			
Constant	-3.341	25.021	24.903
	[0.096]**	[0.924]**	[0.935]**
Observations	10,923	10,923	10,923

Standard errors in brackets, * significant at 5%; **significant at 1%.

Table 2.4: The Effect on Utility in Terms of Dollars

	Static Model	Dynamic Model
Distance from seat to home plate (every 100 feet)	-9.09	-10.26
First floor relative to the second floor	17.55	19.97
Against divisional opponent	8.91	24.65
Against league opponent	-11.63	-15.10
Saturday game relative to weekday game	-36.82	-101.04
Sunday game relative to weekday game	-20.64	-35.85

is no need to include dummies for different days before the event. We can see that the estimated parameters are really similar between the second column and the third column. Those dummies included in the second column are all statistically insignificant.

In the static demand estimation, price and distance from seat to home plate negatively affect the mean utility, and the first floor contributes positively to the mean utility. The average own price elasticity is around -0.42. Using the coefficient on other attributes divided by the coefficient on price, we can measure other attributes of seats by dollars, as shown in Table 2.4. On average, the effect of distance on utility is around -\$9.09 every 100 feet from home plate. Sitting on the first floor have a utility gain around \$17.55, relative to those on the second floor. For instance, seats in area 3 and area 5 have similar distance from home plate, but areas 3 and 5 are on the first and second floor, respectively. Consequently, the average price of seats in area 3 is around \$10 higher than that in area 5.

In addition, different games also contribute differently to the mean utility. Relative to opponents in the same league, consumers value games against the other league \$11.64 higher. Conditional on opponents in the same league, facing opponents in the same division can increase the consumer's utility by \$8.91. Besides the different opponents, the event time can also affect the mean utility. Because the utility of outside good for games on the weekend is higher than that during the weekday, consumers who attend the game on the weekend have lower utility, compared with those who attend the weekday games. Furthermore, purchasing in the differing markets can also determine the mean utility of consumers. People prefer go to the secondary market to buy tickets because the secondary market dummy positively contributes to the utility, and the value of coefficient can be explained as the brand loyalty to StubHub.

Compared with the static demand model, coefficients estimated by the dynamic model in column (3) all have the same sign as those in the static demand model. However, the coefficient of price is -0.078, which is more sensitive to the utility than that in the static demand model. Similarly, the effect of distance on utility is around -$10.26 every 100 feet from home plate. Consumers value sitting in the lower deck/first floor nearly $20 more than sitting in the upper deck. Attributes of games also affect the mean utility as that in the static demand model.

Moreover, the secondary market dummy plays an insignificant role on the dynamic demand estimation. The reason might be that prices in the two markets do not have significant difference for consumers in the dynamic view. In the static model, there exists the price gap between two markets in each period, so it is necessary to use the secondary market dummy to explain the market preference. In the dynamic model, consumers can forecast the future price and buy tickets in the future, and prices in the two markets might be similar in the future. Thus, there is no price difference in the two markets if we consider the prices over time.

2.6 Counterfactual Experiment

This section presents the simulated results when the franchise changes the uniform price schedule into the descending prices as the event approaches. To understand the implication of new prices provided by the franchise, the responses of consumers and secondary market sellers should be considered. Based on the estimated demand system and the behavior of sellers in the secondary market, the new equilibrium can be obtained, and the new revenue for the franchise can be compared with the original revenue.

In the demand side, I assume that the taste of consumers does not change, so the market share can be predicted by the estimated demand system even though some characteristics are changed exogenously. For the supply side in the secondary market, sellers follow the expected profit maximization problem as equation (2.13) to decide the price in each period. From the data, the expected value for sellers in area j after the period t can be obtained by equation (2.16). In the counterfactual experiment, I assume that the expected values for sellers after each period are the same as before. Then sellers in the secondary market can change their prices in response to the new demand.

Table 2.5 and Table 2.6 present the expected values for sellers after each day prior to the game. For each period and each area, the expected values are solved game by game, and the table shows the mean and standard deviation of expected values for 80 games. For those games with higher prices, sellers also have higher expected values.

Furthermore, I do not solve the expected value period by period, using the assumption that the last period's expected value is zero. Therefore, the expected value might be positive or negative, only representing the relative value over time for sell-

Table 2.5: Expected Value for Sellers in the Secondary Market Over Time (Recovered Using the Static Demand Model)

Days Prior to Game	Area 1	2	3	4	5	6	7
1	-41.75	-54.16	-63.13	-67.49	-72.80	-80.22	-72.56
	(20.09)	(17.30)	(12.45)	(13.61)	(9.35)	(9.37)	(10.77)
2	-37.62	-51.09	-59.89	-64.17	-69.91	-77.98	-69.13
	(21.68)	(15.99)	(13.08)	(12.69)	(10.30)	(9.09)	(10.57)
3	-32.53	-48.16	-57.03	-61.81	-68.47	-76.81	-68.80
	(21.49)	(16.61)	(13.01)	(12.21)	(9.59)	(9.63)	(10.90)
4	-30.00	-47.15	-55.70	-60.96	-65.58	-76.12	-66.51
	(23.52)	(18.63)	(13.39)	(14.11)	(8.36)	(9.93)	(10.72)
5	-28.68	-43.94	-54.95	-59.53	-66.04	-75.90	-66.95
	(22.37)	(17.03)	(15.18)	(13.48)	(9.80)	(10.02)	(10.50)
6	-28.17	-44.93	-53.99	-59.55	-65.25	-75.22	-64.67
	(23.49)	(18.18)	(14.57)	(13.45)	(9.08)	(9.44)	(12.30)
7	-27.37	-43.92	-53.20	-59.11	-66.81	-75.08	-65.63
	(23.96)	(16.68)	(15.74)	(13.21)	(10.94)	(9.62)	(12.32)
8	-23.54	-42.29	-51.26	-56.34	-63.11	-74.48	-63.52
	(21.80)	(20.48)	(15.17)	(13.61)	(9.56)	(9.50)	(11.20)
9	-22.48	-41.38	-49.57	-56.23	-63.95	-73.47	-63.65
	(24.49)	(18.37)	(14.07)	(12.62)	(9.31)	(9.16)	(10.83)
10	-20.54	-41.57	-48.12	-55.93	-62.52	-73.49	-62.78
	(27.54)	(19.32)	(15.41)	(13.93)	(11.77)	(9.12)	(11.24)
11	-24.24	-37.78	-44.32	-54.63	-61.64	-72.98	-63.03
	(21.51)	(17.05)	(17.54)	(13.35)	(11.55)	(9.48)	(9.81)
12	-23.64	-35.99	-49.63	-56.76	-61.21	-72.30	-60.74
	(24.31)	(19.98)	(16.00)	(13.17)	(12.79)	(10.39)	(11.28)
13	-22.33	-38.91	-49.54	-57.32	-62.89	-73.55	-61.95
	(22.79)	(19.32)	(15.03)	(14.65)	(13.69)	(10.96)	(12.39)

Standard deviations in parentheses.

Table 2.6: Expected Value for Sellers in the Secondary Market Over Time (Recovered Using the Dynamic Demand Model)

Days Prior to Game	Area 1	2	3	4	5	6	7
1	41.05	28.29	18.99	15.50	8.77	3.29	9.13
	(19.09)	(16.53)	(11.94)	(12.47)	(9.42)	(8.32)	(10.68)
2	44.89	30.97	21.90	18.26	11.68	4.78	12.41
	(20.81)	(15.49)	(12.87)	(12.06)	(10.34)	(8.50)	(10.40)
3	49.55	34.17	24.56	20.58	13.21	5.97	12.63
	(21.04)	(15.65)	(12.67)	(11.62)	(9.50)	(8.40)	(10.73)
4	52.14	34.87	25.87	21.28	15.81	6.56	14.97
	(22.52)	(17.63)	(13.01)	(13.85)	(8.27)	(8.67)	(10.42)
5	53.20	37.85	26.67	22.60	15.15	6.88	14.42
	(21.77)	(16.33)	(14.57)	(12.79)	(9.73)	(8.41)	(10.44)
6	53.96	36.89	27.45	22.47	15.95	7.08	16.52
	(22.90)	(17.47)	(13.92)	(13.20)	(9.16)	(9.16)	(12.11)
7	54.61	37.92	28.08	23.15	14.49	7.49	15.68
	(23.21)	(16.09)	(15.55)	(13.05)	(10.94)	(8.99)	(12.19)
8	58.26	39.36	30.03	25.55	18.06	7.74	17.63
	(21.13)	(19.80)	(14.79)	(13.53)	(9.57)	(8.64)	(11.21)
9	59.06	40.18	31.74	25.75	17.34	8.43	17.53
	(23.88)	(17.72)	(13.80)	(12.08)	(9.33)	(8.66)	(10.61)
10	60.88	39.93	33.10	25.78	18.57	8.68	18.27
	(27.05)	(19.08)	(15.22)	(13.60)	(11.58)	(8.63)	(11.04)
11	57.41	43.52	36.96	27.02	19.43	9.25	18.21
	(20.79)	(16.95)	(16.92)	(12.55)	(11.38)	(8.07)	(9.58)
12	58.09	45.27	31.67	25.04	20.00	9.87	20.44
	(23.43)	(19.72)	(15.53)	(12.09)	(12.09)	(8.64)	(10.69)
13	59.50	42.67	31.74	24.46	18.13	8.69	19.19
	(21.74)	(18.78)	(14.84)	(13.79)	(13.35)	(9.17)	(11.99)

Standard deviations in parentheses.

ers. As indicated in Table 2.5, the expected values calculated by the static demand model are all negative, but those calculated by the dynamic demand model are all positive. The patterns in the two kinds of demand model are quite similar because sellers in the secondary market face the same profit maximization problem no matter how consumers behave differently in the demand side.

For different areas, sellers with higher quality tickets, such as tickets in area 1, have higher expected values. In addition, for different days prior to the game, sellers have declining expected values when the event approaches. Because of the limited time to sell, sellers have less opportunity cost over time. That is the reason why the price trend is declining in the secondary market, as mentioned in Sweeting (2012).

The method I use to simulate the new equilibrium is to calculate both the new market share of different areas in the two markets and the new prices in the secondary market repeatedly. More specifically, the first step is to predict the new market share of products by the estimated demand equation after the franchise change the price in the primary market. Second, sellers in the secondary market adjust their prices after knowing the new market share of products. Then for consumers, prices are changed again, and they change the decision again. After the first step and the second step are repeated several times, the new equilibrium can be obtained. In the new equilibrium, sellers still need to satisfy equation (2.16) to price optimally, and consumers follow either the static demand system or the dynamic demand system.

To simplify the counterfactual experiment, some other characteristics of seats except prices are assumed to be the same. This assumption might not be true because the quality of seats might be different after consumers buy more or less in the previous period. In the real data, some characteristics, such as the distance from the seat to home plate, do not vary significantly over time. The most important characteristic for the counterfactual experiment is price; therefore, price is assumed to be the only endogenous variable that should be solved.

Instead of simulating 80 games, I use the average of 80 games' data as one representative game to analyze the implication of price change. In different games, the franchise might face different situations in the secondary market. For instance, for some popular games, prices might increase even in the last few days before the event. In that case, the franchise might not need the descending price to earn more profits. However, the case we might be interested in is the standard game with a descending price trend in the secondary market. Thus, I use the average data to construct the representative game to do the counterfactual experiment.

The disadvantage of using the average data is that simulated data might not be accurate because the average data does not represent any specific game. In order to understand the implication of price change, I simulate two cases for the franchise: one is simulated by the uniform price over time, and the other is simulated by the descending price over time. The revenue difference in these two models can be explained as the implication of price change.

Table 2.7 presents the price implication simulated by the static demand model. The revenue in the true data is calculated directly by the average price and the total quantity in each area, and the total revenue is around \$40,706 for one game. Compared with the true data, the total revenue simulated by the original uniform prices is quite similar, about \$40,398. However, for different areas, quantities might be over or under predicted by the estimated model. If we want to understand the new price implication, the best way is to compare two simulated results by the model.

If the franchise uses the descending prices over time with maximum prices close to the price level in the secondary market and with minimum prices same as the original price level, the number of sales for each area decreases because of higher prices. However, the total revenue can be increased to \$43,197, which is increased by

Table 2.7: Results of Counterfactual Experiments by Static Demand Model

	True Data			Simulated by Static Demand Model						
	Average	Total		Uniform Prices Over Time			Descending Prices Over Time			
Area	Price	Quantity	Revenue	Price	Quantity	Revenue	Price Max	Price Min	Quantity	Revenue
1	68.61	204.34	14,019.88	68.61	154.02	10,567.10	73.89	68.61	151.28	10,673.53
2	47.05	138.20	6,502.29	47.05	170.55	8,024.56	58.25	47.05	163.63	8,365.85
3	36.00	141.92	5,109.74	36.00	180.95	6,515.10	49.94	36.00	171.82	7,045.89
4	23.15	134.00	3,102.39	23.15	186.34	4,314.28	40.06	23.15	174.93	5,102.69
5	31.79	239.91	7,626.43	31.79	169.70	5,394.36	32.96	31.79	169.43	5,460.39
6	13.80	77.95	1,075.87	13.80	174.85	2,413.11	22.99	13.80	169.11	2,900.52
7	21.41	152.70	3,269.50	21.41	148.07	3,170.18	33.40	21.41	141.62	3,648.96
Total			40,706.10			40,398.69				43,197.83

Table 2.8: Results of Counterfactual Experiments by Dynamic Demand Model

	True Data			Simulated by Dynamic Demand Model						
				Uniform Prices Over Time			Descending Prices Over Time			
Area	Price	Quantity	Revenue	Price	Quantity	Revenue	Price Max	Price Min	Quantity	Revenue
1	68.61	204.34	14,019.88	68.61	72.29	4,959.99	73.89	68.61	64.26	4,559.19
2	47.05	138.20	6,502.29	47.05	174.84	8,226.38	58.25	47.05	155.60	8,078.10
3	36.00	141.92	5,109.74	36.00	282.52	10,172.02	49.94	36.00	252.45	10,558.25
4	23.15	134.00	3,102.39	23.15	384.85	8,910.06	40.06	23.15	342.89	10,449.58
5	31.79	239.91	7,626.43	31.79	140.23	4,457.78	32.96	31.79	124.83	4,032.14
6	13.80	77.95	1,075.87	13.80	204.77	2,826.04	22.99	13.80	182.97	3,230.17
7	21.41	152.70	3,269.50	21.41	67.16	1,437.88	33.40	21.41	59.96	1,585.39
Total			40,706.10			40,990.15				42,492.83

$2,799 per game, around 6.93% of original revenues. The equilibrium prices in the secondary market go up for each area. Intuitively, consumers come into the market and only compare those available seats in the current period, so the franchise can price similarly to the price in the secondary market. Even though the market share goes down, the total revenues still increase because of higher prices.

The result predicted by the dynamic demand model is a little bit different from that predicted by the static model. In the dynamic demand model, consumers can predict the future price trend and make a decision of purchasing. In other words, consumers can expect the lower price in the primary market in the future when the franchise uses the descending price trend. Therefore, we expect that the revenue gains in the dynamic demand model would be less than those in the static demand model. As indicated in Table 2.8, compared with the revenue simulated by the uniform price, $40,990, the revenue simulated by the descending price, $42,492, only increased by $1,503 per game. This is around 3.67% of the original revenue, which is smaller than that in the static demand model. In particular, the franchise has the revenue loss in some areas, such as areas 1, 2, and 5. To sum up, the type of consumers does affect the magnitude of dynamic pricing by the franchise, but overall the effect of dynamic pricing is positive on franchise revenue.

2.7 Conclusion

In this chapter, I use Major League Baseball ticket data both in the primary market and in StubHub to study how the franchise can price dynamically over time to increase the revenue. I find that the revenue for the franchise can be increased if the franchise uses the descending price instead of uniform price over time. Even though the number of tickets sold decreases, the revenue can still be increased by higher prices in the early days before the event.

Two different kinds of demand systems are applied to study the effect of dynamic pricing. One is the static demand model, and the other one is the dynamic demand model. In the static demand model, consumers can not make the decision intertemporally, so the franchise can have more revenue gain by the descending price trend because consumers do not compare prices over time. However, in the dynamic demand model, consumers can stay in the market and predict the future available tickets, so the franchise has less revenues than in the static demand model. Of course, compared with the uniform price, the dynamic pricing can increase the revenue in both cases. By the counterfactual experiment, the revenue for the franchise can be increased by around 6.93% if consumers are assumed not strategic in both markets. If the consumers are strategic in waiting for lower prices, the revenue for the franchise can only be increased by around 3.67%.

In addition, this chapter provides a method for the franchise considering the secondary market reaction to study the price implication. The model captures the competition between two markets and the response of sellers in the secondary market; therefore, it also can be applied for any other industry with the following characteristics: perishable goods selling in a limited time and lots of sellers in a prevalent secondary market. So facing the popular secondary market competition, those franchises in any kinds of sports leagues can obtain more ticket revenue by implementing dynamic pricing for their tickets. The future research can extend this model in two different directions. First, it is worth discussing more comprehensive price schedule for different types of games to further increase the revenue for the franchise. Second, considering the effect of season ticket can make the franchise understand more about the cost of dynamic pricing.

3. PRICING STRATEGIES FOR DIFFERENT TYPES OF SELLERS ON STUBHUB

3.1 Introduction

New trading platforms on the internet provide customers with opportunities to trade tickets online. In the sports ticket market, there are many famous online secondary markets, including eBay and StubHub. Before the game day, the reseller can post a listing with all the ticket information including a listing price and then adjust the price everyday until the game. Different types of resellers face different concerns in determining listing prices. This chapter aims to study how these different types of resellers in the secondary market price their tickets dynamically over time before the game.

Compared with eBay, StubHub has become the more professional platform for selling sports tickets. For each venue and game, StubHub has different web pages with detailed stadium map to show where your tickets will be in relation to the field. This allows sellers to list their tickets easily and for consumers to search the tickets with a clear understanding of where their seats will be. In order to attract the sellers and ensure them they can make a profit, StubHub provides the comprehensive transaction records for the seller to set up the initial price, and the seller can easily change the listing price at any time before the game. Unlike eBay which reveals the rating of the sellers, no information about each seller is provided on StubHub. StubHub also takes a commission after the ticket is sold.

In this chapter, I use both the listing and transaction data on StubHub for the home games of one anonymous Major League Baseball team to investigate the pricing strategies of those sellers. Figure 3.1 shows the average listing and transaction prices

Figure 3.1: Listing and Transaction Prices Over Time

for the two weeks before the game. Both the listing and transaction prices decrease over time until the game day. Compared with the face value, the average listing price is around two times face value two weeks before the game day, and then it falls to the face value on the last day. Most of the sellers change the prices frequently as the game day approaches. Figure 3.2 presents the average number of tickets available and the actual transaction quantities per game over time. The number of tickets listed per game is between 2000 and 2500, and most of the sellers post their listings earlier. As the game day approaches, the number of tickets available decreases, and the number of transactions increases.

Not all the sellers have the same purpose in selling their tickets. Some might want to sell their tickets simply because they cannot attend the game, yet some sellers might want to make profits through the online secondary market. Therefore,

Figure 3.2: Listing and Transaction Quantities Over Time

heterogeneous sellers can have different pricing strategies in different aspects. I have classified the sellers into two groups: single sellers and brokers. Those who sell tickets only in one or two games during the whole season are defined as the single sellers, and those sellers who sell many tickets in one game and sell tickets in most of the games in the season are defined as brokers. Because the data allow me to identify how many tickets they buy in the primary market, the two types of sellers can be classified according to the detailed purchasing information.

Comparing the price levels over time for the two types of sellers, I find that the listing prices set by the brokers are relatively lower than those set by the single sellers on the final day. However, on other days before the game, the brokers prices are significantly higher than those of the single sellers even though the quality of tickets is controlled.

Having said that, only comparing the price level is not enough. I also estimate the probability of sale for each listing on each day to calculate the optimal prices. The optimal prices vary depending on the days before the game and the seats relation to the field. The brokers tend to price more optimally with less expected profit losses on the last day than do the single sellers. Beyond that, the two types of sellers have similar expected profit losses on other days before the game.

The remainder of this chapter is organized as follows. Section 3.2 reviews the literature related to dynamic pricing. Section 3.3 summarizes the data I use in this chapter. Section 3.4 presents the model for estimating the probability of sale and calculating the optimal prices. Section 3.5 shows the results. Section 3.6 concludes the research.

3.2 Literature Review

In this section, I briefly review the literature on dynamic pricing, which is also called revenue management in some economics and marketing literature.

Monopolistic dynamic pricing models, starting with Gallego and van Ryzin (1994), consider how a monopoly firm sell perishable goods in a limited time under stochastic demand. Customers are assumed to arrive according to a Poisson process, and the monopoly firm decides the price for each period to maximize the revenue. The optimal pricing strategy can be characterized as a function of the inventory and time left in the horizon (Bitran and Mondschein, 1997). Bitran and Caldentey (2003) and Elmaghraby and Keskinocak (2003) provide a comprehensive survey to classify different models. Zhao and Zheng (2000) extend the model by considering the generalized demand system with consumers whose reservation price distribution changes over time.

Aside from the monopolistic dynamic pricing models, there is an extensive literature on competitive revenue management. Netessine and Shumsky (2005) study a static quantity-based competition between two airlines. Prices are the same for each airline, but the airlines need to decide how many seats to reserve for higher-fare passengers. Perakis and Sood (2006) present a multiple-period pricing model to characterize the dynamic pricing problem under oligopolistic competition. Lin and Sibdari (2009) study a discrete-time model under the multinomial logit demand, and they proves the existence of Nash equilibrium when the inventory levels for each firm are assumed as public information. Xu and Hopp (2006) use a continuous model to study oligopolistic competition, and they establish a weak perfect Bayesian equilibrium for the pricing game. In addition, dynamic pricing under competition can also be extended to different directions, such as capacity constraint (Martínez-de Albéniz and Talluri, 2011) and strategic consumers (Levin, McGill, and Nediak, 2009; Deneckere and Peck, 2012).

Empirical literature on dynamic pricing also refers to price discrimination. However, most of the empirical studies focus on airline markets. For instance, Escobari (2012) finds that the price increases as the inventory decreases, and the price decreases while there is less time to sell. Furthermore, literature also indicates that businessmen and leisure travelers are two types of consumers for the firm to enact price discrimination. In the hotel industry, Lee, Garrow, Higbie, Keskinocak, and Koushik (2011) find that the price does not increase as the arrival date approaches. In the apparel industry, Heching, Gallego, and van Ryzin (2002) find that smaller mark-down pricing can raise the revenue significantly in the early sales season, but Soysal and Krishnamurthi (2012) show that strategic consumers delay their purchases and lower the retailer's revenues. Facing strategic consumers, retail revenues are 9% lower than they would have been while consumers are non-strategic. In the sports ticket secondary market, Sweeting (2012) finds that prices are decreasing over time as the game date approaches, and the sellers lower the price because of the decreasing opportunity cost of holding tickets. Moreover, he uses data to test how accurately dynamic pricing models describe sellers' behavior, and he proves that simplest dynamic pricing models can fit the behavior of sellers very well, and consumers are not strategic in buying tickets in the secondary market.

The analysis in this chapter is similar to that of Sweeting (2012), but the study further discusses the heterogeneity of sellers. Most of the literature assumes that sellers price optimally based on the remaining horizon. However, different types of sellers might have different pricing decisions which cause them to deviate from the optimal strategies. Therefore, this chapter uses the comprehensive data to answer this question.

3.3 Data

The data I use contain all the listing and transaction information on StubHub from March 25, 2011 to September 28, 2011 for some home events of one anonymous Major League Baseball franchise in 2011 season.[1] Because of the detailed primary market transaction data, the seller can be identified if the listing contains the specific seat information. The listing data are observed daily on StubHub.

Table 3.1 shows the summary statistics for the information of listings on StubHub, including the listing prices, days prior to the game, sold status, face values, and other characteristics for quality. Each observation is an available seat daily observed on StubHub within two weeks before the game. Because the seller on StubHub tends to set a higher price in the beginning and lower the price everyday until the game. The mean listing price is \$55.97, which is higher than the mean face value, \$35.63. The listing prices vary based on both the quality of tickets and the timing of listing. The

[1] In order to have all the listings until the day of the event, only 31 home events are included in the data. Most of the games happened in the first half of the season before August.

standard deviation of listing prices is \$33.41 making it greater than the standard deviation of face values. The quality characteristics include the distance from seat to home plate, row number, and front row of section dummy. In addition, not all of the listings reveal the seat number, so only parts of the listings can be identified by the purchasing records in the primary market. Approximately 77.1% of listings allow us to identify the information of sellers.

Table 3.1: Summary Statistics for Listings

	Obs.	Mean	Standard Deviation	Max	Min
Listing prices (\$ per seat)	973,347	55.970	33.441	449	0.01
Days prior to game	973,347	7.537	4.123	14	0
Listing sold dummy	973,347	0.056	0.231	1	0
Face value (\$ per seat)	973,347	35.627	18.997	95	12
Distance from seat to home plate	973,347	269.749	95.306	439.3	72.81
Row numbers	973,347	9.431	7.959	41	1
Front row of section dummy	973,347	0.102	0.303	1	0
With account information	973,347	0.771	0.420	1	0

Because the primary market transaction data include comprehensive information of purchasing, we can understand how many tickets sellers bought in this season, what kinds of channels they used to buy tickets in the primary market, the prices they pay for tickets, and the zip code they live in. Table 3.2 shows the summary statistics for those identified sellers where each observation is a seller observed on StubHub. The total number of identified sellers is 8,606. Some of the sellers only have tickets in one or two games, but some have tickets in almost every game in the season. The average number of games sellers have tickets is around 37.59, and the average number of tickets they have in one season is around 166.16. However, not

Table 3.2: Summary Statistics for Sellers

	Obs.	Mean	Standard Deviation	Max	Min
Number of games holding tickets	8,606	37.585	31.546	81	1
Number of tickets in one season	8,606	166.159	481.758	33,002	1
Number of listings listed	8,606	12.801	32.494	847	1
Number of tickets listed	8,606	39.757	147.695	6,481	1
Buying tickets in the primary market by					
single game tickets	8,606	0.275	0.446	1	0
package tickets	8,606	0.467	0.499	1	0
group tickets	8,606	0.030	0.170	1	0
multiple types with package	8,606	0.214	0.410	1	0
multiple types without package	8,606	0.006	0.074	1	0
three mixed types	8,606	0.010	0.099	1	0
Distance from home to stadium (miles)	5,770	112.628	274.471	1,866	0.000457
Single sellers	8,606	0.603	0.489	1	0
Brokers	8,606	0.003	0.056	1	0

all their tickets are listed to resell on StubHub. The average number of listings in one season on StubHub is around 12.80, with about 39.76 tickets for one seller. The most active seller posts 6,481 tickets in 61 games using 847 listings.

In addition, people can buy tickets in the primary market through three different avenues: single game tickets, package tickets, and group tickets. In Table 3.2, 46.7% of the sellers buy the package tickets and resell parts of their tickets on StubHub, and 21.4% of sellers buy tickets by the multiple types, including the package tickets. This means the tickets on StubHub are mostly from the package tickets. Furthermore, 27.5% of the sellers buy the single game tickets in the primary market. For various reasons, the sellers may have different pricing strategies. Although prices in the primary market are considered as sunk costs for the sellers, different types of the tickets might also reveal some information about the sellers. For those sellers who want to gain the profits through the resale, they need to consider using a lower cost to buy tickets in the primary market. However, for those who simply cannot attend the game, this may not have been a consideration when purchasing.

In order to classify sellers more robustly, I use records from the whole season to define the two types of sellers more specifically. The single sellers have fewer than 5 listings on StubHub per season; the brokers have more than 200 listings and sell over 70% of their tickets. By the definition, Table 3.2 shows that around 60% of sellers are the single sellers, while only 27 sellers fit into the brokers category (0.3% of all the sellers). Although the number of the brokers is small, they have many listings in the market. Among the 27,837 listings on StubHub, there are 2,540 listings from the brokers (9.12% of all the listings), and there are 2,778 listings from the single sellers (9.98% of all the listings).

Figure 3.3 shows the median listing prices, which are not adjusted by quality, for the single sellers and brokers within two weeks before the game. On the last day, the median listing prices for both types of sellers are close to the face value. However, on other days prior to the game, the price levels for the two types of sellers vary. Prices for the brokers are systematically 0.5 times face value higher than those for the single sellers. The median price for the brokers is about two times the face value two weeks prior to the game, whereas the median price for the single sellers only starts from around 1.5 times the face value.

Table 3.3 represents the regression results after adjusting for quality by controlling for the distance from seat to home plate, row number, front row of section dummy, area dummies, and game dummies. The first two columns list the regression results without the quality adjustment. Those sellers not specified as single sellers or brokers

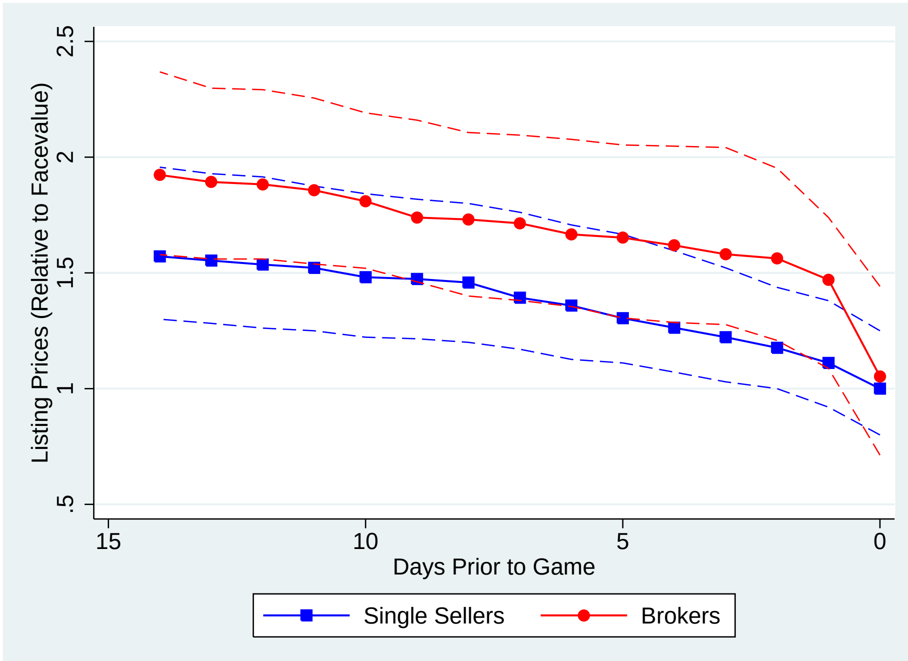
Table 3.3: Prices Difference Between Single Sellers and Brokers Over Time

	Dependent Variable: Listing Prices			
Compared with the benchmark	(1)		(2)	
Days prior to game	Single sellers	Brokers	Single sellers	Brokers
0	-0.00229	-0.00993	0.0843***	-0.171***
	[0.0156]	[0.0132]	[0.0139]	[0.0118]
1	-0.0622***	0.183***	-0.0857***	0.194***
	[0.0210]	[0.0174]	[0.0187]	[0.0155]
2	-0.0992***	0.244***	-0.111***	0.270***
	[0.0205]	[0.0169]	[0.0183]	[0.0150]
3	-0.106***	0.243***	-0.131***	0.282***
	[0.0205]	[0.0166]	[0.0182]	[0.0148]
4	-0.104***	0.221***	-0.139***	0.265***
	[0.0205]	[0.0164]	[0.0182]	[0.0146]
5	-0.102***	0.187***	-0.137***	0.234***
	[0.0207]	[0.0162]	[0.0184]	[0.0144]
6	-0.103***	0.199***	-0.129***	0.250***
	[0.0208]	[0.0162]	[0.0185]	[0.0144]
7	-0.100***	0.216***	-0.126***	0.267***
	[0.0210]	[0.0161]	[0.0187]	[0.0143]
8	-0.0836***	0.197***	-0.112***	0.245***
	[0.0212]	[0.0160]	[0.0188]	[0.0142]
9	-0.0935***	0.260***	-0.118***	0.308***
	[0.0212]	[0.0159]	[0.0189]	[0.0142]
10	-0.106***	0.286***	-0.129***	0.336***
	[0.0214]	[0.0159]	[0.0190]	[0.0142]
11	-0.102***	0.331***	-0.129***	0.376***
	[0.0216]	[0.0159]	[0.0192]	[0.0141]
12	-0.0997***	0.340***	-0.128***	0.385***
	[0.0216]	[0.0159]	[0.0192]	[0.0141]
13	-0.101***	0.333***	-0.126***	0.380***
	[0.0217]	[0.0159]	[0.0193]	[0.0141]
14	-0.0931***	0.404***	-0.125***	0.451***
	[0.0219]	[0.0159]	[0.0194]	[0.0141]
Constant	1.099***		1.758***	
	[0.00503]		[0.00835]	
Quality control			Yes	
Observations	750,727		750,727	
R-squared	0.073		0.267	

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 3.3: Median Listing Prices for Single Sellers and Brokers



are called the benchmark group. Compared with the benchmark group, there is no difference for the single sellers or the brokers on the last day. However, during days 2-14 prior to the game, the single sellers have a lower price level as shown in Figure 3.3, and the brokers have an overall higher price level.

The third and fourth columns represent the results after the quality control. The result indicates that on the last day, the prices listed by the single sellers are around 8% of face value higher than those by the benchmark group, and the prices listed by the brokers are 17% of face value lower than those by the benchmark group. Thus, considering the quality control, the brokers do price around 25% of face value lower than the single sellers on the last day. However, on other days before the game, the prices for brokers are relatively higher than those for the single sellers even after we have controlled the quality of the tickets.

3.4 Model

3.4.1 Seller's Problem

For a given game g, there are T periods, indexed by t={1,2,...T}, for the sellers to sell their tickets, and the game starts after the period T. The sellers might come into the market at different time, but in each period the number of sellers is large enough, which the market power for each seller is relative small in the market. However, because of the heterogeneous tickets, each seller can still decide the price in every period which maximizes the expected profits. In the model, each seller is assumed to have only one ticket when coming into the market, and we assume there is no switching cost to adjust the price everyday until the game. The model is very similar to section 2.4.3, but the difference is that tickets are heterogeneous within the same area according to the distance from seat to home plate and different row numbers. In addition, sellers are assumed not homogeneous in the market, so we solve each seller's optimal problem to decide the optimal price for each listing on each day.

For a seller k coming into the market at period t, the profits maximization problem can be written as

$$\max_{p_{kt}} p_{kt}\Phi_{kt}(p_{kt}) + (1 - \Phi_{kt}(p_{kt}))EV_{kt+1}, \ t = 1, 2, ..., T \tag{3.1}$$

where $\Phi_{kt}(p_{kt})$ is the probability of sale when seller k decides the price p_{kt} at period t, and EV_{kt+1} is the value of the ticket after period t. Because the quantity provided by each seller is relative small in the market, we can assume that the probability of sale $\Phi_{kt}(p_{kt})$ is exogenous for each seller, which we can estimate that from all the listings in the market.

In the last period T, the value EV_{kT+1} can be explained as the remaining value of the ticket after the game starts. Some people might be able to attend the game even if they can not resell their tickets in the secondary market, so the remaining value should be positive for them. However, some people, such as brokers, have too many tickets in one game, so they might have zero remaining values for most of the tickets. As there is no good proxy for the remaining value for those people who can still attend the game, I calculate the optimal price for each ticket by assuming that the remaining values are zeros.

The first order condition for profits maximization problem is

$$\Phi_{kt}(p_{kt}) + \frac{\partial \Phi_{kt}(p_{kt})}{\partial p_{kt}}(p_{kt} - EV_{kt+1}) = 0, \ t = 1, 2, ..., T. \tag{3.2}$$

By assuming the remaining value of the ticket $EV_{kT+1} = 0$, we can solve backwards and find the optimal prices p^*_{kt} from period T to period 1, and the optimal value for each period is

$$EV^*_{kt} = p^*_{kt}\Phi_{kt}(p^*_{kt}) + (1 - \Phi_{kt}(p^*_{kt}))EV^*_{kt+1}, \ t = 1, 2, ..., T. \tag{3.3}$$

3.4.2 Probability of Sale

In order to obtain the probability of sale for each ticket in each period, I specify a probit model as the following:

$$s^*_{kt} = \beta_0 - \alpha p_{kt} + x_{kt}\beta + u_{kt}, \tag{3.4}$$

$$p_{kt} = x_{kt}\Pi_1 + z_{kt}\Pi_2 + v_{kt}, \tag{3.5}$$

where $s_{kt} = 1\{s^*_{kt} \geq 0\}$ represents the sale of listings, and x_{kt} includes the distance from seat to home plate, row number, front row of section dummy, area dummies, and game dummies to characterize the quality of seats.

In the secondary market, the prices set by the sellers might be correlated with some unobserved demand shock u_{kt}, so equation (3.5) specifies a cost-based shock to solve the endogeneity problem. The instrument variable z_{kt} includes the original price in the primary market, the distance of the seller's zip code from the stadium, and the ticket types that the seller buys in the primary market. All of the variables represent the seller's cost of buying tickets and the opportunity costs of sale. Those variables should not be correlated with the unobserved demand shock because the seller purchases the ticket earlier.

In addition, u_{kt} and v_{kt} are jointly distributed according to a joint normal distribution:

$$\begin{pmatrix} u_{kt} \\ v_{kt} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma_v \\ \rho\sigma_v & \sigma_v^2 \end{pmatrix}\right), \tag{3.6}$$

where $\rho = 0$ if there is no endogeneity problem. If considering the endogeneity problem, I use the control function approach to estimate the model. [2] If there is no endogeneity problem, the model can be estimated by equation (3.4) using probit model. In order to estimate the probability of sales on different days more flexibly, I separately estimate the IV probit model day by day until the game day.

[2]In order to confirm the validity of the model, I also compare this with the two stage least square linear probability model, and the results are similar.

3.5 Estimation and Results

3.5.1 Estimation Results

The estimates are shown in Table 3.4. Different columns represent different days before the game. For the coefficients on price, we find that price is most sensitive on the last day and least sensitive 5 days before the game, showing that the demand becomes more elastic as the game day approaches. In addition, all the characteristics contribute more to the probability of sale on the last day. Conditional on the same area and the same game, seats with longer distance from home plate and larger row number have less probability of sale, and the front row seats have higher probability of sale.

3.5.2 Comparison of Actual Listing Prices to Optimal Prices

Based on the estimates from Table 3.4, we can calculate the optimal price for each ticket on each day by equations (3.2) and (3.3). Figure 3.4 shows the optimal and listing prices for brokers in the last five days before the game. Because the listing data contain some extremely high prices, I present the 25 percent quantile, median, and 75 percent quantile in the following analysis. From 5 days before the game to the game day, the optimal prices for the brokers decrease over time. The listing prices set by the brokers are significantly higher than optimal though the price pattern over time is closer to the optimal one.

In Figure 3.5, the listing price pattern is different from the optimal price pattern for the single sellers. Between 1 and 5 days prior to the game, the single sellers tend to follow the optimal pricing pattern. However, on the last day, the single sellers tend to price significantly higher than optimal. Single sellers, unlike brokers, are more likely to attend the game if they do not sell the tickets, so they may have a positive "residual value". If we rationalize the behavior of the single sellers on the

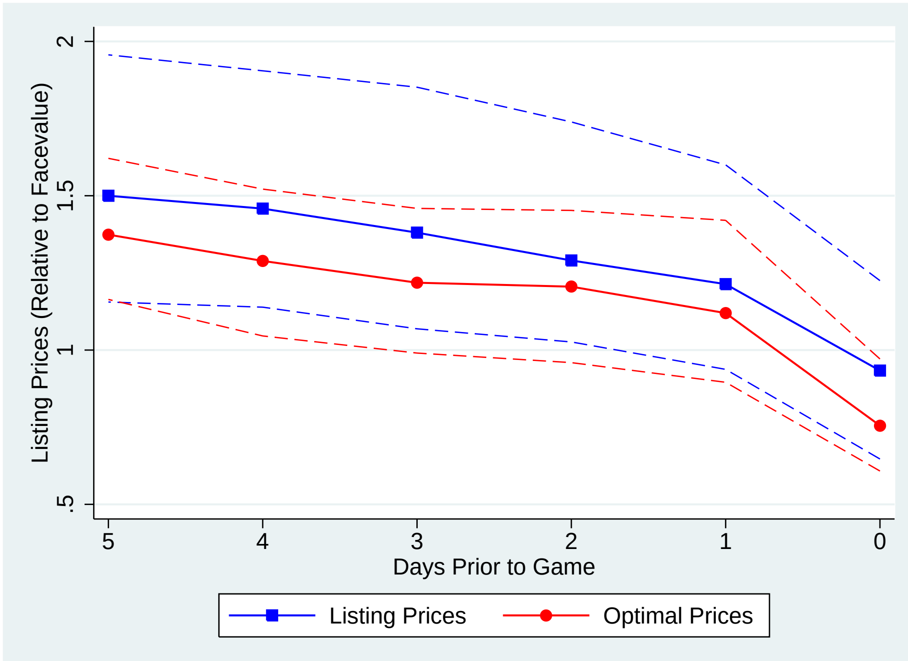
Table 3.4: Estimates for Probability of Sale by IV Probit Model

	Days Prior to Game					
	0	1	2	3	4	5
	IV Probit	IV Probit	IV Probit	IV Probit	IV Probit	IV Probit
Price	-2.893	-1.395	-1.271	-1.452	-1.427	-1.094
	[0.099]***	[0.151]***	[0.107]***	[0.103]***	[0.095]***	[0.105]***
Distance from seat to home plate	-0.00404	-0.00483	-0.00303	-0.00326	-0.00380	-0.00104
	[3.50e-04]***	[4.18e-04]***	[4.05e-04]***	[4.39e-04]***	[4.30e-04]***	[4.67e-04]**
Row number	-0.032	-0.011	-0.008	-0.016	-0.005	-0.008
	[0.002]***	[0.002]***	[0.002]***	[0.002]***	[0.002]**	[0.002]***
Front row of section	0.387	0.272	0.079	0.376	0.310	0.195
	[0.034]***	[0.049]***	[0.048]	[0.051]***	[0.051]***	[0.054]***
Area dummies	Yes	Yes	Yes	Yes	Yes	Yes
Game dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.789	2.321	0.972	1.302	1.582	0.495
	[0.184]***	[0.306]***	[0.230]***	[0.229]***	[0.217]***	[0.251]**
Observations	21725	28663	33510	35939	38028	39566

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

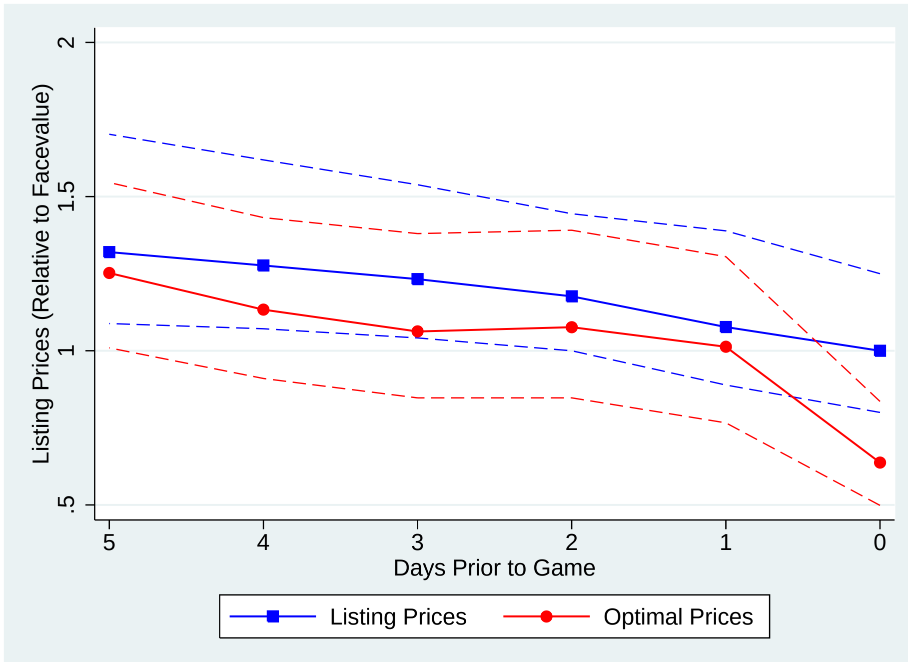
Figure 3.4: Listing and Optimal Prices for Brokers



last day by assuming the positive remaining values after the game day, the optimal prices during the 1-5 days prior to the game should also be shifted upward by the positive remaining values. Then, single sellers would also deviate from the optimal prices during 1-5 days prior to the game. As a result, the single sellers either price higher than the optimal price on the last day or deviate from the optimal pattern during the earlier days.

If we focus on the last day and calculate the difference between the actual listing prices and the optimal prices generated by the model, Figure 3.6 shows the Kernel Density function of the difference between single sellers and brokers. For most of the listings set by the brokers, the prices are close to the optimal level, making the differences close to zero. However, the single sellers tend to price higher than the optimal level on the last day, so the Kernel Density function of the difference shifts

Figure 3.5: Listing and Optimal Prices for Single Sellers



from zero to positive.

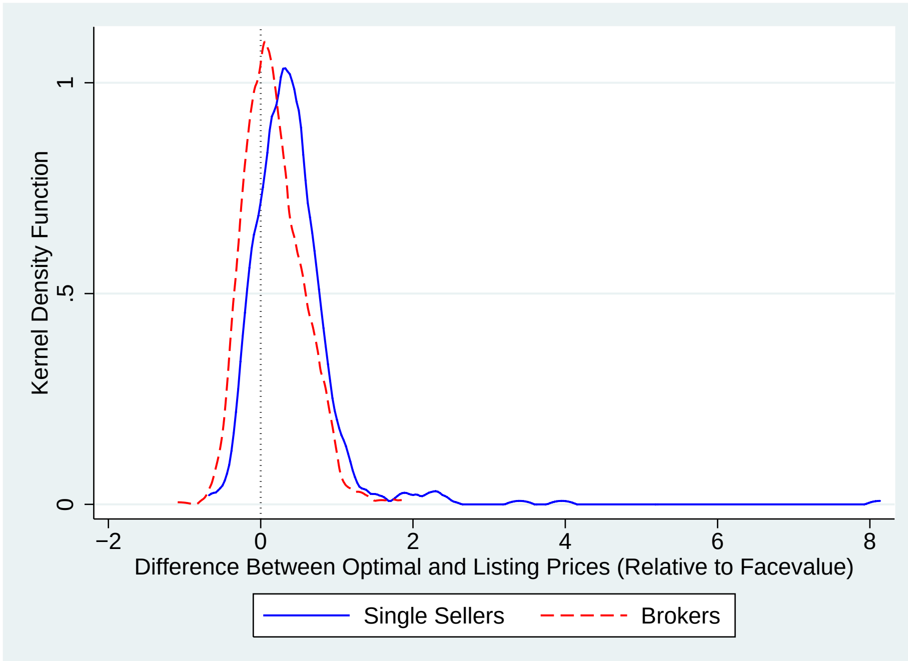
Another way to compare the actual listing prices with the optimal prices is to calculate the expected profit loss for each listing. As the seller decides the price in the secondary market, the difference between the optimal expected profits (π^*) and the actual expected profits (π^a) could be explained as the "expected profit loss" for the seller. So the expected profit losses are calculated by:

$$\pi^*_{kt} - \pi^a_{kt}, \tag{3.7}$$

where

$$\pi^a_{kt} = p^a_{kt}\Phi_{kt}(p^a_{kt}) + (1 - \Phi_{kt}(p^a_{kt}))EV^*_{kt+1}, \ t = 1, 2, ..., T, \tag{3.8}$$

Figure 3.6: Difference Between Optimal and Listing Prices on Game Day



and p_{kt}^a is the actual listing price for seller k at time t.

Figure 3.7 and Figure 3.8 show the median expected profit losses for the single sellers and brokers. In Figure 3.8, we can find that single sellers have the expected profit losses over 10% of face value on the last day. Figure 3.7 also shows that listings for the single sellers have the higher expected profit losses than those for the brokers on the last day, and the difference between two types of sellers in the expected profit loss is around \$1.31. On other days before the game, the expected profit losses are close to zero for two reasons. The first reason is that the probability of sale within 1 to 5 days prior to the game is not high enough. This means deviating pricing strategies might not have a significant losses on that day. The second reason is that the sellers are still assumed to price optimally in the next few periods, so the expected profits on that day could be close to optimal because the optimal pricing

Figure 3.7: Expected Profit Losses (Dollars)

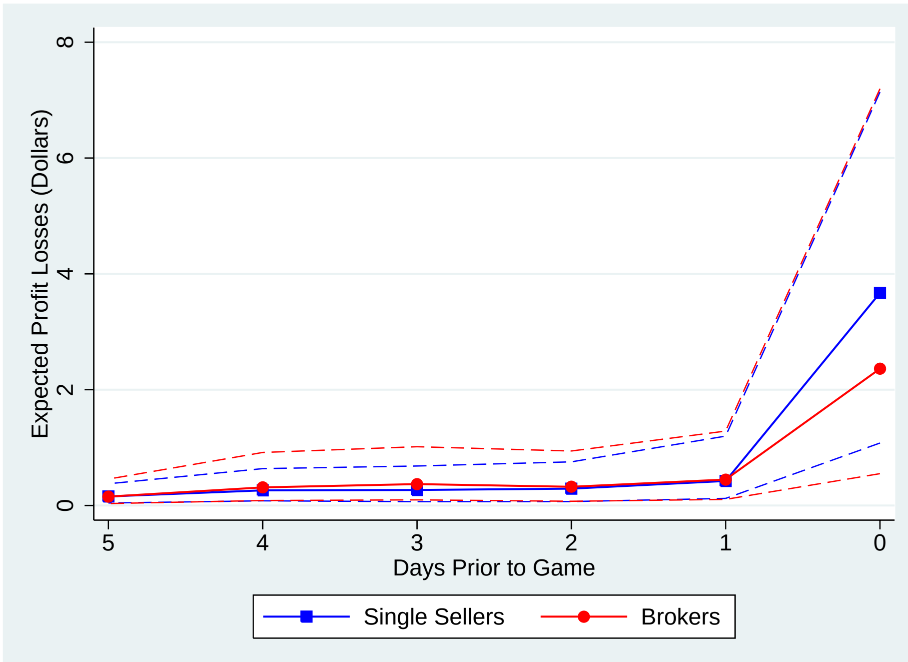


Figure 3.8: Expected Profit Losses (Relative to Facevalue)

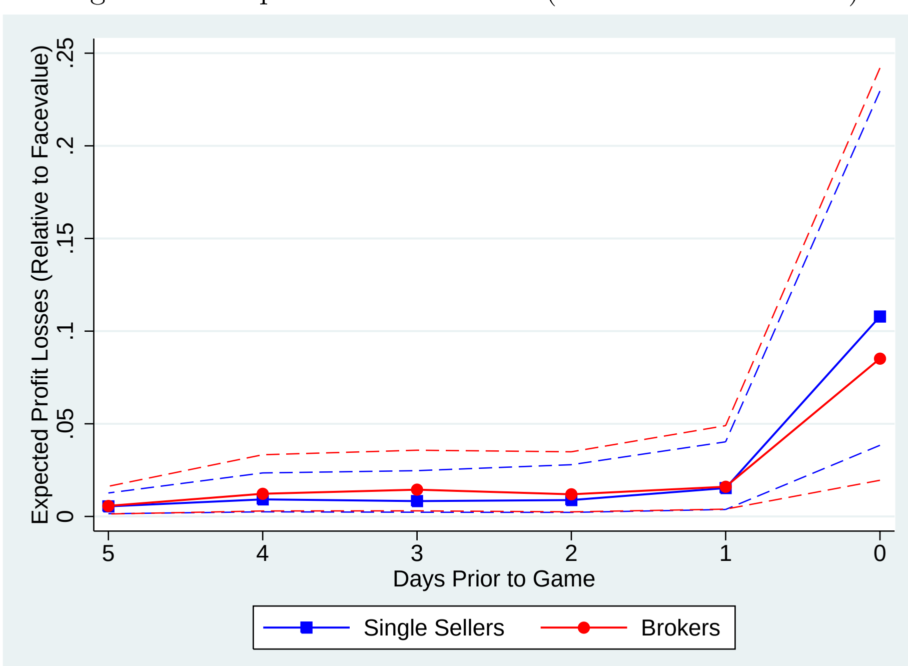
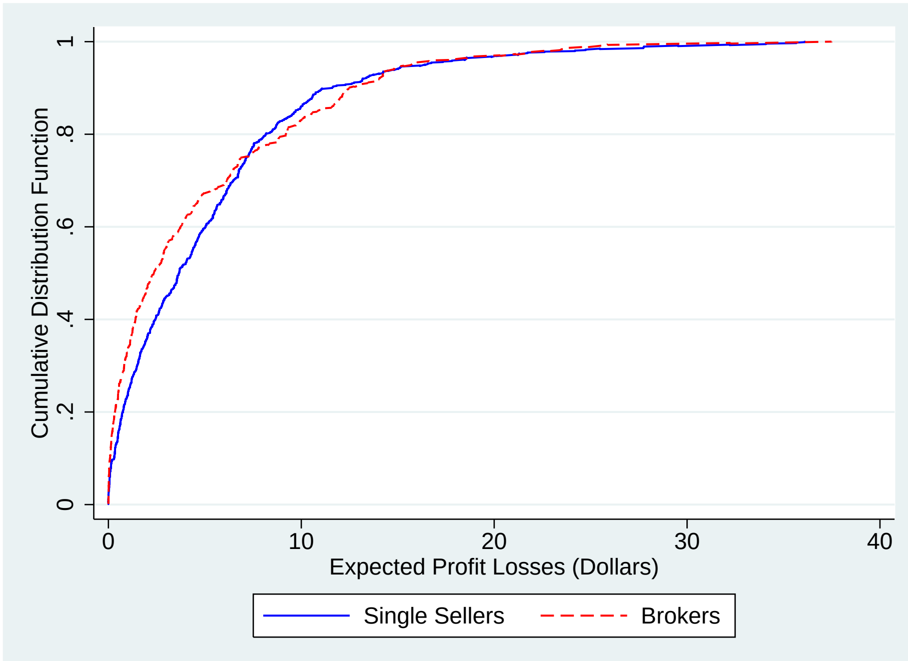


Figure 3.9: Cumulative Distribution Function for Expected Profit Losses on Game Day



strategy in the next few periods would not have any loss.

Figure 3.9 presents the cumulative distribution function of expected profit losses for the single sellers and brokers on the last day. Compared with the single sellers, the brokers have more listings with an expected profit loss of less than 5 dollars. However, the index of expected profit losses still has some disadvantages. For instance, for those listings with a higher face value, the larger optimal expected profits can cause higher expected profit losses. Therefore, I have created another index which is called the "expected profit loss rate" to measure how many percentage of expected profits the seller expects to lose. The expected profit loss rate is defined as

$$\frac{\pi^*_{kt} - \pi^a_{kt}}{\pi^*_{kt}}. \tag{3.9}$$

Figure 3.10: Expected Profit Loss Rate

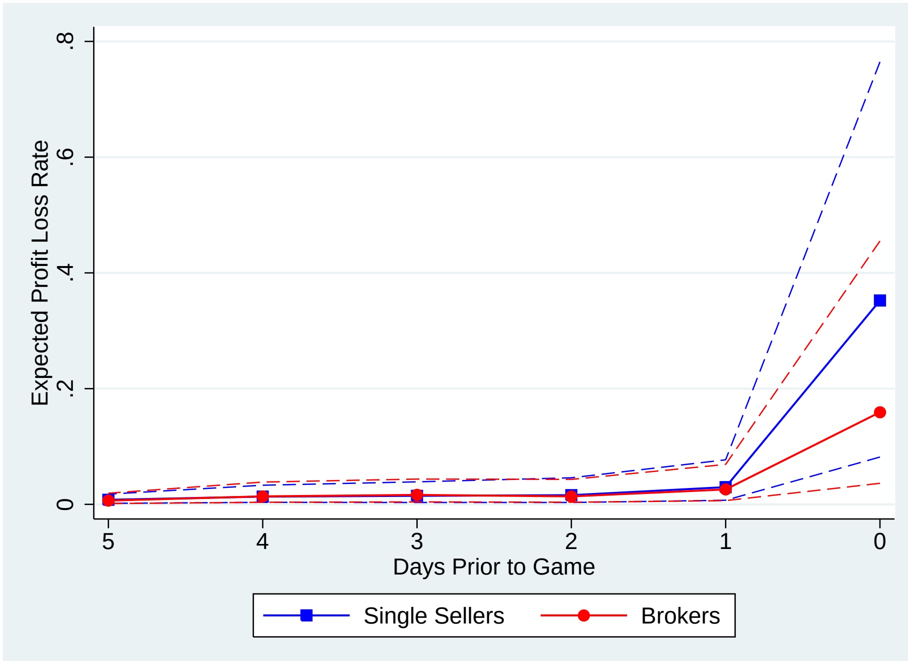
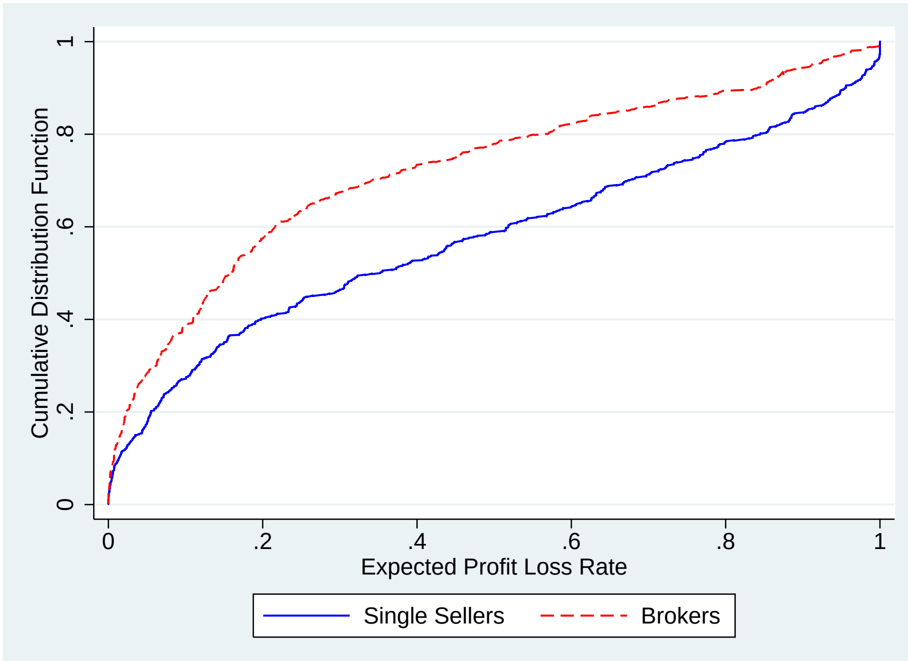


Figure 3.10 shows the expected profit loss rate for the different types of sellers 5 days leading up to the game. The biggest difference between two types of sellers is the loss rate on the last day. The single sellers tend to have a higher loss rate than the brokers. The cumulative distribution function in Figure 3.11 clearly indicates that the brokers can always price more optimally and have less expected profit loss rate for their listings.

3.5.3 Discussion

Three possible reasons can explain the difference between the actual listing prices and the optimal prices. The first is the positive remaining values of the tickets. The optimal prices increase if the seller has the positive remaining values after the game day. In Figure 3.5, the difference on the last day can be rationalized by the positive remaining values for the single sellers. If we focus on those single sellers who live far

Figure 3.11: Cumulative Distribution Function for Expected Profit Loss Rate on Game Day



from the stadium, then the difference becomes smaller on the final day.

The second one is the cost of changing list price – or a "menu cost". Actually, the switching cost includes the menu cost and the management cost where we had before assumed zero. For instance, sellers need the time to observe other information and to decide the price. Switching cost would cause the actual listing prices up and down the optimal prices; however, the data show that only some sellers do that on days leading up to the game.

The third possible reason is a bounded rationality explanation. For example, considering the reference price could cause the optimal price shift to the reference price, whereas the reference prices would be the price in the primary market or the transaction price on the previous day. In Figure 3.5, we can find that the single sellers tend to price above the face value even on the final day.

3.6 Conclusion

In this chapter, I use both listing and transaction data on StubHub to study different pricing strategies for different types of sellers. The data show that the sellers on StubHub can be separated into two types: single sellers and brokers. The single sellers sell tickets in one or two games during a season, and the brokers sell many tickets in one given game and also sell tickets in most of the games during the season. I use the data to estimate the probability of sale by the probit model and calculate the optimal prices for each listing on each day. The brokers do price more optimally with the less expected profit losses and even less expected profit loss rate on the last day than do the single sellers. In addition, during other days before the game, two types of sellers have the similar expected profit losses, which are close to zero. Three possible reasons to explain the difference between the actual listing prices and the optimal prices can be tested in the future study.

4. CONCLUSION

In this dissertation, I discuss dynamic pricing issues not only in the primary market for the franchise but also in the secondary market for the different types of resellers. In the first essay, I use Major League Baseball ticket data from one anonymous franchise in the 2011 season to study how the franchise can price dynamically to increase its revenue. I find that the revenue for the franchise can be increased if the franchise uses the descending price instead of uniform price over time. Even though the number of tickets sold decreases, the revenue can still be increased by higher prices in the early days before the event. Compared using a uniform price schedule over time, the revenue for the franchise can be increased by around 6.93% if consumers are assumed not strategic in both markets. However, if consumers are strategic in purchasing tickets, the revenue for the franchise can only be increased by around 3.67%.

In the second essay, I use both listing and transaction data on StubHub to study different pricing strategies for the different types of sellers. The data show that the sellers on StubHub can be separated into two types: single sellers and brokers. The single sellers sell tickets in just one or two games during the whole season. The brokers sell many tickets in a given game and also sell tickets in most of the games during the season. In addition, I use the data to estimate the probability of sale by the probit model and calculate the optimal prices for each listing on each day. The benchmark model shows that brokers do price more optimally with the less expected profit losses and even less expected profit loss rate on the last day than do the single sellers. In addition, during other days before the game, two types of sellers have the similar expected profit losses, which are close to zero.

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