Effect of Resale on Optimal Ticket Pricing: Evidence from Major League Baseball Tickets

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Abstract

I use Major League Baseball ticket data, both in the primary market and in StubHub, for 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, the revenue for the franchise can be increased by decreasing prices as the game date approaches in a manner estimated by my model. In the counterfactual experiment, 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%.

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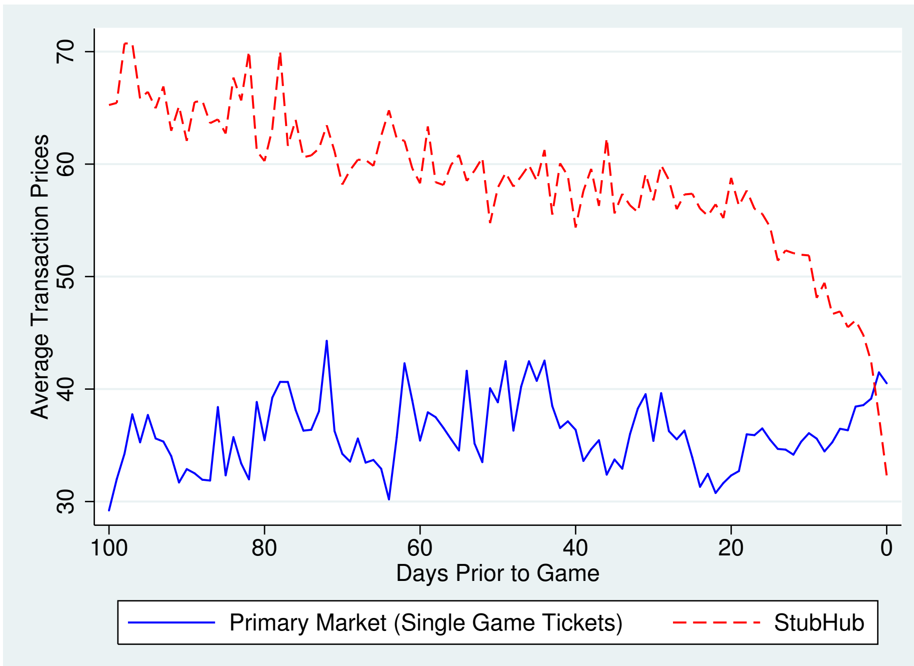
1 Introduction

Professional sports are widely popular in the United States, and because of the convenience of the internet, people can buy tickets online at any time not only from the official team website but also from other online marketplaces. In addition, sellers can adjust their listed prices frequently in the market; therefore, the dynamic pricing issues have recently become more popular and important in the sports ticket market. In other industries, such as the hotel and airline industries, the dynamic pricing issues have been broadly discussed in the literature and applied in the real world. However, there exists the secondary market for resale in the sports ticket market. It is necessary to consider the secondary market when we discuss the dynamic pricing issue for the franchise in the primary market. This research aims to investigate how the franchise can optimally price tickets when resale is quite prevalent in the secondary market.

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 pricing differently to fit the demand 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 one is widely used for all franchises, and recently most franchises have started to have different price menus for each game. However, the third one, dynamic pricing over time, is rarely used for franchises so far. 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

Figure 1: Average Prices in Both Markets Over Time



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 paper, 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.

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 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 we can find the price difference between the two markets in Figure 1, there is almost no cost for consumers to choose tickets between them. 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 the 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 the revenue. In the static demand model, the 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 paper 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 the article is organized as follows. Section 2 reviews the related literature. Section 3 summarizes the data in both markets. Section 4 presents the model including the demand side and the supply side. Section 5 shows the estimation method and results. Section 6 provides the counterfactual experiment based on the result of demand estimation. Section 7 concludes the research.

2 Literature Review

In this section, two groups of literature related to ticket pricing are introduced. First, I mention some literature using the 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) uses second-degree price discrimination to discuss how the monopoly franchise prices tickets under the deterministic demand. Dana (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 the 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) finds the same effect of price discrimination in the concert tour data.

As the resale becomes prevalent in the market, more and more literature starts to discuss the resale effect 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) proposes 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 the 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 the 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 (2013) uses 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.

Unlike the previous literature which nest 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.

3 Data

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.

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 1 shows the average number of tickets sold in the two markets and only presents

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

Table 1: Mean Number of Tickets Sold Over Time in the Two Markets

Days Prior to Game	Primary Market: Single Game Tickets	Primary Market: Package Tickets	StubHub
0	566 (2)		623
1-7	779 (40)		1,694
8-14	503 (40)	20 (2)	540
15-30	1,403 (284)	52 (7)	617
31-60	1,200 (176)	265 (43)	550
61-100	1,012 (198)	704 (108)	358
101+	2,699 (532)	23,817 (2,979)	325
Total	8,162 (1,272)	24,858 (3,139)	4,707

Note: The numbers in parentheses represent the average number of tickets bought in the primary market at that time and resold in the secondary market later on. I use the listing information on StubHub to indicate whether the ticket sold in the primary market is resold or not. Because I only observe one secondary market, StubHub, those numbers are underestimated.

the number of single game tickets and package tickets for the primary market.[2] As indicated in Table 1, over 50 percent of package tickets are sold early in the season, about over 100 days before the game. However, on StubHub, over 50 percent of the transactions happen within two weeks before the event. To capture the competition between these two markets, the transaction data in the last two weeks are used to estimate the demand. The earlier transaction data in the primary market (first 60 days) are used to estimate the cost of resale for brokers, so the initial stock of secondary market listings is endogenous.

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 instrument variable I mention

[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 1.

in section 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 value.

Table 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 the 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.

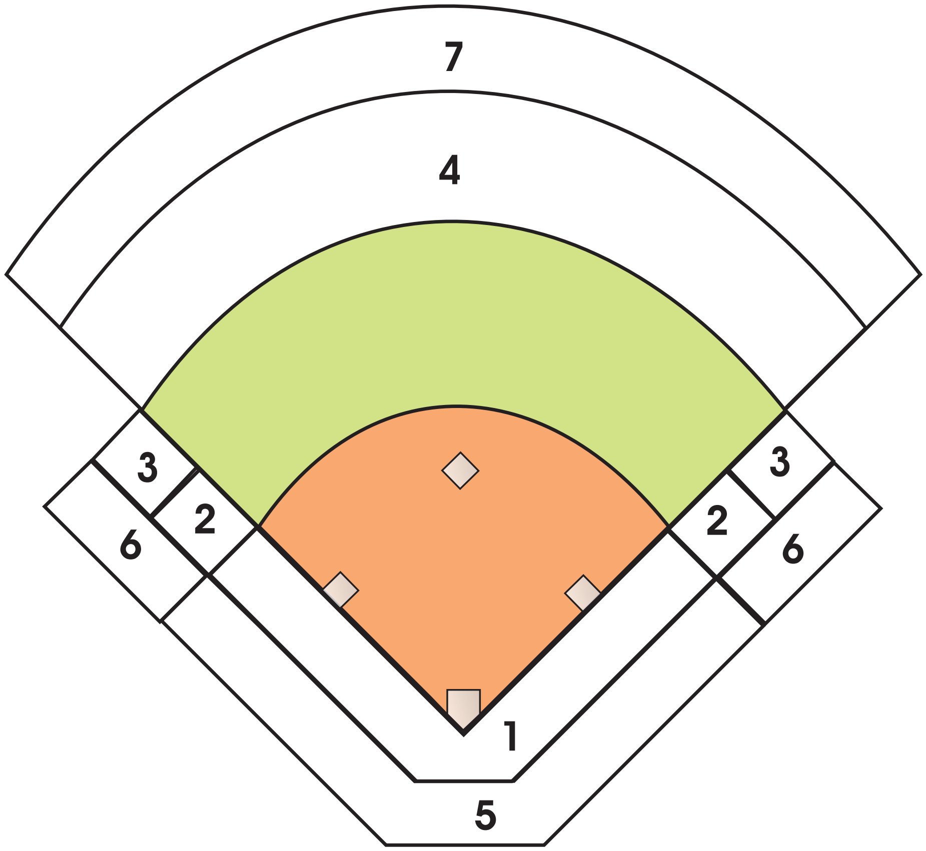
If we focus on the sample in 1-13 days prior to the game, exclude those transactions with extreme high prices, drop those tickets in some special areas, and exclude the data from the home opener, the summary statistics are shown in the bottom part of Table 2. The average number of transactions in the primary market is 729.26 per game, less than 1589.09 on StubHub. Consumers tend to buy ticket 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

[3] See section 3.2.

Table 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

Figure 2: Area Location in the Baseball Field

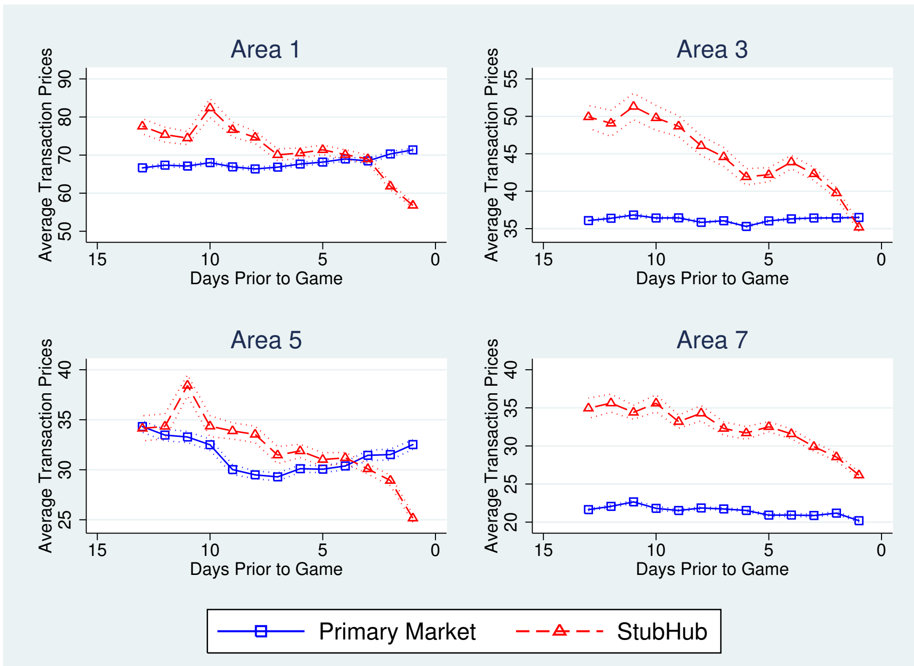


is higher on StubHub, tickets sold in the secondary market are distributed amongst the areas with lower face values. In addition, prices in the secondary market still vary larger than those in the primary market because of the descending price trend on StubHub. The maximum transaction price on StubHub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

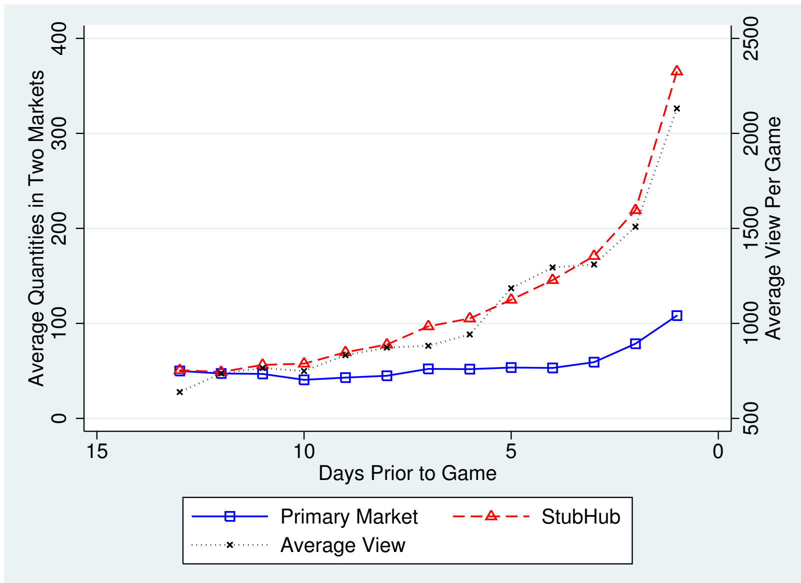
Figure 3: Prices for Different Areas in the Two Markets Over Time



patterns on StubHub are also various in different areas. Figure 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 1 can also be explained as the composition of the tickets sold, Figure 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 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 on StubHub.

Figure 4: Average View and Quantity in Both Markets Over Time



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.

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. Although the pricing pages are referred to the primary market, it can be explained as the number of potential consumers if we believe that consumers can switch two markets without any cost. Figure 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 over 2000 on the last day before the game. Furthermore, in Figure 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 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 instrument variable (See section 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.

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.

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 $t = \{0, 1, 2, ..., T\}$, and the game starts after the last period $t = T$. In each period, there are N_t potential buyers coming into the market. In period 0, only the primary market opens, and there is no secondary market in period 0. From period 1 to T, the market contains both the primary market and the secondary market. Also, there are two groups of buyers: consumers and brokers. The purpose of consumers is to purchase a ticket for the event, so assume that they don't resell the tickets. Because brokers try to resell the tickets to obtain the profits, assume that they only show up in period 0. In the following analysis, I use the subscript i for consumers and b for brokers.

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

Consumers start to buy tickets from the first period $t = 0$. 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. 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. 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

$$u_{ijt} = \gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + \mathbf{D}_t\boldsymbol{\gamma}_2 + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

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 shock 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

$$s_{jt} = \frac{\exp\{v_{jt}\}}{1 + \sum_{k=1}^{J_t} \exp\{v_{kt}\}}, \quad \forall t = 1, 2, ..., T. \tag{2}$$

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

$$s_{0t} = \frac{1}{1 + \sum_{k=1}^{J_t} \exp\{v_{kt}\}}, \quad \forall t = 1, 2, ..., T. \tag{3}$$

Brokers have the heterogeneous cost τ_b to resell their tickets. The cost of reselling tickets is distributed in log normal distribution, which $\log(\tau_b) \sim N(\mu_\tau, \sigma_\tau^2)$. Brokers also have the same expectation on future price $\bar{r}_j$ in the secondary market for area j. The expected profit for broker b buying the ticket for area j at period 0:

$$\pi_{bj} = \bar{r}_j - p_{j0} - \tau_b + \nu_{bj},$$

where ν_{bj} are idiosyncratic error terms for brokers, is distributed i.i.d. according to Type I extreme value distribution.

In the data, the number of tickets from the primary market which are resold later on in the secondary market can be directly obtained, so assume that a fraction θ of buyers are brokers, and a fraction $1-\beta$ are consumers. Then the market share of area j at period 0 is

$$s_{j0} = \beta \int_{\tau_b} \frac{\exp\{\bar{r}_j - p_{j0} - \tau_b\}}{1 + \sum_k \exp\{\bar{r}_j - p_{j0} - \tau_b\}} + (1-\beta)\left(\frac{\exp\{v_{j0}\}}{1 + \sum_k \exp\{v_{k0}\}}\right).$$

The market share of area j and the market share of outside goods is observed from the data.

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 $\epsilon_{it} = (\epsilon_{i0t}, \epsilon_{i1t}, ...\epsilon_{iJ_t t})$ 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

$$V_i(\epsilon_{it}, \Omega_t) = \max\Big\{\epsilon_{i0t} + \beta E[V_i(\epsilon_{it+1}, \Omega_{t+1})|\Omega_t], \max_{j=1,\dots,J_t}\{v_{jt} + \epsilon_{ijt}\}\Big\}, \tag{4}$$

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 (4) 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

$$\delta_t = \ln\Big(\sum_{j=1}^{J_t} \exp\{v_{jt}\}\Big). \tag{5}$$

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:

$$\text{EV}(\Omega_t) = \ln\Bigg(\exp\Big(\beta E[\text{EV}(\Omega_{t+1})|\Omega_t]\Big) + \exp(\delta_t)\Bigg), \tag{6}$$

where $\text{EV}(\Omega_t) = \int_{\epsilon_{it}} V(\epsilon_{it}, \Omega_t)$ 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 $\text{Prob}(\Omega_{t+1}|\Omega_t) = \text{Prob}(\delta_{t+1}|\delta_t)$. 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:

$$\delta_{t+1} = \pi_0 + \pi_1 \delta_t + \eta_t. \tag{7}$$

Then the market share of area j at period $t \in (0, T]$ is

$$s_{jt} = \frac{\exp\{v_{jt}\}}{\exp\big\{\beta E[\text{EV}(\delta_{t+1})|\delta_t]\big\} + \sum_{k=1}^{J_t} \exp\{v_{kt}\}}. \tag{8}$$

In period 0, based on the purchase by brokers, the market share of area j at period 0 is

$$s_{jt} = \beta \int_{\tau_b} \frac{\exp\{\bar{r}_j - p_{j0} - \tau_b\}}{1 + \sum_k \exp\{\bar{r}_j - p_{j0} - \tau_b\}} + \Bigg(\frac{(1-\beta)\exp\{v_{j0}\}}{\exp\big\{\beta E[\text{EV}(\delta_1)|\delta_0]\big\} + \sum_{k=1}^{J_0} \exp\{v_{k0}\}}\Bigg). \tag{9}$$

The value function, equation (6), can also be written as:

$$\mathrm{EV}(\delta_t) = \ln\Bigg(\exp\Big(\beta E[\mathrm{EV}(\delta_{t+1})|\delta_t]\Big) + \exp(\delta_t)\Bigg). \tag{10}$$

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):

$$v_{jt}^{\text{new}} = v_{jt}^{\text{old}} + \psi\Big(\ln\left(\bar{s}_{jt}\right) - \ln\left(\hat{\bar{s}}_{jt}(\mathbf{v}^{\text{old}})\right)\Big), \quad \forall\, j, t, \tag{11}$$

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 (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 (5) in each period t. Also, $\hat{\pi}_0$ and $\hat{\pi}_1$ can be estimated by equation (7). Then I discretize δ_t into 50 grid points.[5] Based on $\hat{\pi}_0$ and $\hat{\pi}_1$, the transition matrix can be obtained for each state. Given the initial guess of the value function $\mathrm{EV}(\delta_t)$, the new value function is iterated by equation (10). Once we have the true value function for each state, the market share can be predicted by equation (8).

Then we can have the estimated equation as

$$v_{jt} = \gamma_0 - \alpha p_{jt} + \mathbf{x}_{jt}\boldsymbol{\gamma}_1 + \mathbf{D}_t\boldsymbol{\gamma}_2 + \xi_{jt}, \tag{12}$$

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 (**??**) and (12), I use the Generalized Method of Moment (GMM) to deal with the endogeneity problem. (See section 5)

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

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

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

$$\max_{p_{kt}} p_{kt}\Phi_{kt}(p_{kt}, p_{-kt}) + (1 - \Phi_{kt}(p_{kt}, p_{-kt}))EV_{kt+1}, \tag{13}$$

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.

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:

$$\Phi_{kt}(p_{kt}, p_{-kt}) + \frac{\partial \Phi_{kt}(p_{kt}, p_{-kt})}{\partial p_{kt}}(p_{kt} - EV_{kt+1}) = 0. \tag{14}$$

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

$$p_{kt}^* = EV_{kt+1} + \frac{\Phi_{kt}(p_{kt}^*, p_{-kt}^*)}{\left|\frac{\partial \Phi_{kt}(p_{kt}^*, p_{-kt}^*)}{\partial p_{kt}}\right|}. \tag{15}$$

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:

$$p_{jt}^* = EV_{jt+1} + \frac{s_{jt}(p_{jt}^*, p_{-jt}^*)}{\left|\frac{\partial sjt(p_{jt}^*, p_{-jt}^*)}{\partial p_{jt}}\right|} \quad \forall\ j = 1, 2, ...J_t, \tag{16}$$

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.

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 $\mathcal{J}_{0t} = \{\ j \mid \forall j \text{ in the primary market at time } t\}$. 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 $\mathcal{J}_0 = \{\ j \mid \forall j \text{ in the primary market}\}$. The revenue under the original price menu $\{p_j\}_{j\in\mathcal{J}_0}$ should be

$$\sum_{t=1}^T \sum_{j\in\mathcal{J}_0} N_t s_{jt}(p_{jt}, p_{-jt})p_{jt}. \tag{17}$$

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

$$\max_{\{\{p_{jt}\}_{j\in\mathcal{J}_{0t}}\}_{t=1}^T} \sum_{t=1}^T \sum_{j\in\mathcal{J}_{0t}} N_t s_{jt}(p_{jt}, p_{-jt})p_{jt}. \tag{18}$$

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 6, I use a new price menu to calculate the revenue and compare that with the original one.

5 Estimation and Results

5.1 Endogeneity Problem

The demand can be estimated by equation (**??**) and (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 instrument variable for the demand in the secondary market. The instrument 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. In the primary market, they have already used the cheaper price to buy tickets, and they can share the risk by selling multiple game tickets. As a result, for those areas with higher proportion of sellers holding package tickets, the average transaction price is also lower.

Moreover, we need to check 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 in the beginning of the season. The only chance for the cost shifter to be correlated with the unobserved demand shock is if sellers decide to resell their tickets based on the information of unobserved demand shock. From the data

I can observe that those sellers 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 instrument variable to identify the demand.

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 instrument variable and other exogeneous variables in the secondary market. The sample moment condition is

$$\mathbf{m}(\alpha, \boldsymbol{\gamma}) = \begin{bmatrix} \frac{1}{n_0}\mathbf{z}_0'\boldsymbol{\xi}_0(\alpha, \boldsymbol{\gamma}) \\ \frac{1}{n_1}\mathbf{z}_1'\boldsymbol{\xi}_1(\alpha, \boldsymbol{\gamma}) \end{bmatrix}, \tag{19}$$

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

$$\left(\hat{\alpha}, \hat{\boldsymbol{\gamma}}\right) = \arg\min_{\alpha, \boldsymbol{\gamma}} \mathbf{m}(\alpha, \boldsymbol{\gamma})' W \mathbf{m}(\alpha, \boldsymbol{\gamma}), \tag{20}$$

where W is a weighting matrix.

The estimated parameters are shown in Table 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 is no need to include dummies for different days before the event. We can see that the estimated

Table 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	-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 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

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 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, opponents in a different league can let consumers obtain the utility gain around \$11.64. 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) are all with 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. Sitting in the first floor has about \$19.97 effect on the mean utility of consumers. 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.

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 (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 (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 5 and Table 6 present the expected values for sellers after each day prior

Table 5: Expected Value for Sellers in the Secondary Market Over Time (Recovered using the Static Demand Model)

Days	Area						
Prior to Game	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 6: Expected Value for Sellers in the Secondary Market Over Time (Recovered using the Dynamic Demand Model)

Days	Area						
Prior to Game	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.

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 sellers. As indicated in Table 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 (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 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 \$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 8, compared with the revenue simulated by the uniform price,

Table 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 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		Quantity	Revenue
							Max	Min		
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

\$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.

7 Conclusion

In this paper, 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 paper provides a method for the franchise considering the secondary market reaction to study the price implication. The model provides 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. 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.

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