Season Ticket Buyer Behavior and Secondary Market Options

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Abstract: Sports franchises derive significant portions of their revenues from season ticket holders who pre-purchase tickets with large price discounts but significant uncertainty of game quality. A recent trend that may have meaningful consequences for season ticket management is the development of legitimate secondary markets. This research investigates the value of secondary markets to season ticket holders. We find that, on one hand, secondary markets provide an option value to list tickets to resell in addition to attendance and forgoing. On the other hand, the secondary markets may attract listing, push down resale prices, and make the resale option unattractive. We assemble a unique panel data that combines season and single ticket purchase records with ticket usage records on attend, forgo, list, and resale. We build a structural model of ticket purchase and usage. Our policy experiments suggest that overall secondary markets increase season ticket purchase rates by 5.97%, equivalent to $2,633,394 revenue increase over 6 years. The impacts of secondary markets are most pronounced for lower quality seat tickets.

Keywords: Secondary Markets, Season Ticket Holders, Ticket Resale

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1. Introduction

Season ticket customers of sports franchises often exhibit strong loyalty and are an important source of team revenues. For example, in the NBA it is estimated that more than 75% of box office revenues come from season ticket buyers (Lombardo 2012). However, consumer's decisions to purchase tickets to sporting events involve a complex set of expectations and options that complicate efforts to create models of consumer demand. First, season ticket buying decisions involve significant uncertainty about product quality since customers purchase season tickets in advance of the events (Moe and Fader 2009; Deisraju and Shugan 1999; Xie and Shugan 2001). In the case of major league baseball, full season ticket packages are purchased before team and opponent quality is revealed over an 81 game schedule. Second, there are also issues related to purchase timing and quantity discounts. Consumers have the option to purchase either single game tickets at full price or season ticket packages at a discount. In terms of timing, season tickets are usually purchased before the season, while single game tickets may be purchased as the season progresses.

A recent trend that may have meaningful consequences for season ticket buyer management is the development of legal and easy to use secondary markets. While informal, and often illegal, secondary markets have long been a feature of the sports business landscape, trusted digital secondary markets such as StubHub are a relatively recent innovation. Markets like StubHub add further complexity to season ticket buyer management. Secondary markets create additional options for consumers that can have complex effects on the value of season tickets. First, a secondary market may have positive consequences on season ticket purchases since consumers can recoup costs by selling unneeded or valuable tickets. The value of reselling can be especially important because season tickets are often purchased at a discount to the single-game prices offered by teams. Alternatively, the secondary market might have a negative impact on season ticket sales if it creates an alternative supply of highly valued or low priced tickets that reduces the need to pre-commit to a large bundle of tickets (Tuchman 2015).

Furthermore, it is important to note that the overall value provided by the secondary market to season ticket buyers may be difficult to assess. Secondary market prices are a function of the aggregate probability of season ticket holders selling their tickets. If many season ticket buyers utilize a secondary market, this may push down resale prices and make the resale option of season tickets less attractive. Whether an efficient secondary markets adds value to season ticket holders depends on the consequences of these counteracting mechanisms. Therefore, it is not straightforward as to whether secondary markets can become a relationship enhancing tool for sports clubs to retain season ticket holders.

The objective of our paper is to investigate how the increased options provided by a secondary market influence the decisions of different types of consumers to purchase bundles of season tickets. We accomplish this objective through a structural model of consumer demand and several counter-factual analyses related to the operation and regulation of secondary markets. To estimate our model, we assemble a unique panel data set by combining consumer ticket transactions with ticket usage records from the seasons from 2011 to 2016 for a major league baseball team. We further augment the buying and usage data with secondary market listing and transaction data from a ticket broker. This provides a complete picture of season ticket holders' game level usage as we are able to observe whether each ticket was used for attendance, listed, resold, or forgone. An additional issue is that there are significant differences in ticket quality and ticket prices within a stadium. To ensure that our model is relevant to the team's customer management efforts, we use observed quality preferences, based on ticket quality levels, as a source of observable heterogeneity.

The complexity of the season ticket buying environment necessitates a sophisticated analysis strategy. We build a structural model of season ticket package purchase and game-level ticket usage decisions in the context of major league baseball. The model is developed around the idea that at the start of season, season ticket purchase decisions are based on the expected utility from planned ticket usage in terms of attendance, reselling or non-usage. Because of the temporal separation of season ticket purchase and actual games, we allow fans to form game quality expectations based on scheduling dates, home and opponent team performance in the last season, and team payrolls for the upcoming season. The model considers the collective utility of the entire 81 game slate. The model is also flexible as it allows for the substitution of sets of single game tickets as a substitute for season ticket packages.

A central challenge in this analysis is modeling the interdependence between the supply of and the demand for secondary market tickets. Our research provides a contribution through the simultaneous modeling of secondary market ticket supply and demand. On the demand side, we model the secondary market ticket resale probability as a function of seat quality, game quality, list prices, and percentage of tickets listed by other season ticket holders. On the supply side, we model the utility of listing as the cost of listing plus a weighted average of the expected value of a successful resale and the maximum value of attending or forgoing when a reselling attempt fails.

In addition to the listing decision we also model the season ticket holder's list pricing decision. Season ticket holders who decide to list a ticket for resale select a game specific list price that maximizes listing utility. We then derive a closed form expression for the probability of listing tickets on the secondary markets that is based on factors such as game quality, secondary market demand parameters, and each seller's price sensitivity and preferences for listing tickets on the exchange. This structure is particularly important in our counterfactual analyses that investigate the impact of limits on minimum or maximum prices. The joint model of supply and demand in the secondary market enables us to compute the market equilibriums in the counterfactual analyses. We estimate the model with an MCMC Bayesian approach. We control for the endogeneity of list prices by treating the market shock realizations as augmented latent variables in the MCMC estimation steps (Yang, Chen and Allenby 2003).

Substantively, we find that the secondary market creates incremental value for season ticket holders and thereby increases season ticket purchase and retention rates. The ability to resell tickets provides a means for season ticket buyers to benefit from unwanted or highly demanded tickets. In terms of the team's customer management metrics, our policy experiments suggest that the secondary market increases season ticket purchasing rates by 5.97%. The effect is smallest for customers that tend to choose the highest quality tickets and becomes more substantial for customers that choose lower quality tickets. The overall impact of the secondary market is an increase in revenue of $2,633,394 for the team over the 6-year window.

We also conduct counter-factual analyses related to the operation and regulation of secondary markets. The legal landscape related to secondary markets varies across states and is evolving (Michaelson 2015). For example, the state of Michigan recently decriminalized the practice of selling tickets above market value (Oosting 2015a, 2015b) and Missouri (AP 2017) is debating legislation that would require venues to offer both transferable and non-transferable tickets. Leagues and teams are also interested in regulating secondary markets for marketing purposes. For instance, the Yankees, the only MLB team that opted out of a partnership with StubHub in 2012, recently reached an agreement with StubHub on the condition that resales cannot occur below a minimum price (USAToday 2016). Additionally, there are several teams that have attempted to limit the use of secondary markets by requiring fans to use preferred or team owned ticket exchanges (Rovell 2015). The NFL has been particularly active in trying to influence the operations of secondary markets by limiting which markets may be used and imposing price floors (Zagger 2017). This variety of legal and marketing interventions highlight the importance of understanding the impact of secondary markets on both teams and season ticket buyers.

In terms of secondary market regulations, we find that a minimum list price policy on secondary market tickets reduces season ticket purchase rates by 2.28%, equivalent to $1,042,918 revenue loss for the team. This "face value" minimum price policy has a particularly large negative impact on low quality season tickets, as these season tickets are more likely to be listed at a lower price ratio relative to gate prices. The importance of the secondary market is further revealed through an analysis that assumes listing becomes easier or less costly in terms of time and effort. This is an important scenario since more efficient mobile applications and user experience is likely to make ticket listing more commonplace and easier over time. In this scenario, season ticket purchase rates increase by 2.70%, and the season ticket revenues increase by $1,088,576 over 6 years. This volume is also concentrated in the lower quality ticket tiers.

The remainder of the paper is as follows. We begin with a brief literature review that highlights several issues related to modeling season ticket holder buying. We then describe the data and present several simple analyses that highlight key behaviors. Section 4 details the model and Section 5 describes the estimation procedure. Section 6 presents the estimation results and Section 7 describes several simulation studies that highlight the impact of the secondary market. We conclude the paper with a discussion related to the opportunities for further research and limitations of the current research.

2. Background

Developing decision support models related to season ticket holder management is challenging because purchases occur in a setting that includes advance buying, bundling and a secondary market. The tracking of ticket usage and resales is also somewhat unique to sports. Most CRM models are limited to purchasing data such as recency, frequency and monetary value measures (Reinartz and Kumar 2003) but the sports category now provides a view of actual product usage (Bolton and Lemon 1999). In addition, customer-reselling activity from the secondary market provides important behavioral data related to preferences. In this section, we review selected literature relevant to these aspects of consumer decision making. The goal is to motivate our empirical specification rather than to exhaustively review the literature.

2.1 Advance Buying

One key aspect of season ticket purchases is advance purchasing. Season tickets are usually purchased in advance of the season, while single game tickets are more often purchased within seasons. The marketing literature has considered the topic of advance buying with an emphasis on exploiting segment differences to maximize firm revenues (Desiraju and Shugan 1999; Xie and Shugan 2001). Moe and Fader (2009) empirically study advance selling in a setting that includes quality based price tiers. Moe and Fader are also notable in that they consider price dynamics.

Advance buying is especially relevant to CRM in sports since tickets are purchased before the quality of the team is fully revealed. In this type of consumer decision making, it is important to explicitly model consumer expectations. One goal of our research is to develop a modeling framework that explicitly accounts for quality expectations across a bundle of items. This is a complex challenge given that bundles of MLB tickets include 81 unique and potentially separable elements. In the context of season ticket holder management, expectations are likely focused on the quality of the home team. If this is the case, then models of season ticket buying should include factors correlated with winning rates such as past success and the payroll of the home team (Lewis 2008). Fans may also form expectations of the quality of a season ticket based on the opponents that are scheduled. From a modeling standpoint, the relevant point is that models of customer buying should account for expectations of season quality.

2.2 Price Bundling and Season Tickets

Season tickets represent a form of bundling where collections of games are sold as a package. Stremersch and Tellis (2002) provide an extensive review on the bundling literature that includes definitions of key bundling terms and propositions that guide optimal bundling techniques for different scenarios.

Several researchers have proposed techniques for optimally setting season ticket prices. For example, Hanson and Martin (1990) formulate the bundle pricing problem as a mixed integer programing problem and investigate a variety of scenarios related to customer reservation prices, firm costs and number of components. Venkatesh and Mahajan (1993) proposed a method for optimally pricing bundles of performances based on customer's time availability to attend events and reservation prices for musical performances. In this application customers' time and pricing preferences were collected via a survey. Ansari et al. (1996) extend Venkatesh and Mahajan's model to also consider decisions regarding the number of events (components) to be held and for alternative objectives such as maximizing attendance. In these models, the primary focus is on the quantity discount aspect of season tickets. The key insight that drives this stream of research is that the valuation of the bundle should consider the cumulative value of the component parts. This literature has not focused on the retention of season ticket holders across seasons.

The sports context includes a number of elements that complicate the analysis of bundling. First, organizations often pursue a mixed strategy where tickets may be purchased through season ticket packages or as single game tickets. This means that the analysis needs to consider the decision between buying the complete package and buying a subset of single game tickets. Second, there has been little discussion in the literature of contexts where product quality of the bundled components is uncertain. At a minimum, this type of structure will complicate model development as it becomes necessary to consider the role of consumer expectations. Third, the existence of a secondary market may have a significant impact on consumer response to bundling. Secondary markets provide an explicit mechanism for consumers to potentially unbundle sets of products. This presents analytical challenges to marketers as it may be necessary to incorporate expectations regarding the secondary market into consumer decision models.

2.3 Secondary Markets and Tickets

In the sports context, there is a limited literature focused on secondary ticket markets. For instance, Sweeting (2012) examines the relationship between secondary markets and teams' dynamic pricing policies. Sweeting (2012) provides both theoretical explanations and empirical evidence related to pricing patterns over time. In the context of the 2007 major league baseball, Sweeting finds that secondary market sellers cut prices by 40 percent or more as time to event decreased. Xu, Fader and Veeraraghavan (2016) study the revenue implications for teams that adopt dynamic pricing. They leverage a natural experiment where a baseball franchise changed from a fixed pricing policy to a dynamic pricing policy. They find that dynamic pricing may increase a franchise's revenue by up to 15%. Zhu (2014) presents an aggregate structural model of consumer ticket purchase decisions of buying from StubHub versus teams. Zhu finds that optimal dynamic pricing by a team only results in an increase in revenue of 3.67%. In contrast, we take a different perspective by focusing on the micro foundations of consumer decision making. We focus on how season ticket package value is altered by the options to unbundle packages and resell tickets provided by the secondary market.

Leslie and Sorensen (2014) examine the ticket resale markets in the context of single events. They focus on the welfare implications of ticket resale markets using data on rock concerts. However, they do not explicitly model the interdependence between resale prices and listing. This is important because as resale prices increase there is likely to be an endogenous increase in the utility of listing, which may increase the utility of buying season ticket packages. We propose a structural model to simultaneously consider ticket supply and aggregate demand in the secondary market. This supply and demand structure facilitates counterfactual analyses related to the value of secondary markets to season ticket holders under different rules of market operation.

Two recent related papers investigate the option value of secondary markets (Ishihara and Ching 2017; Shiller 2013). Ishihara and Ching (2017) model the role of used markets on new goods sales in the context of Japanese video games. In this model, in each period consumers decide to purchase new, or used video games, or not purchase. Conditional on previous purchase, consumers decide to sell or not. This model includes important elements of consumer dynamics. When buying a video game, consumers are assumed to be forward-looking in terms of expected resale value. This is an important aspect of consumer behavior that should be included in a season ticket package buying model. However, our context and model are different from theirs in key aspects. For example, season tickets are bundles of perishable items rather than a durable item such as a video game. This changes key elements of the decision related to purchase timing and requires that any modeling effort considers the option to separate the season ticket package into component parts. The common practice of discounting season tickets is also a relevant distinction.

Season ticket prices are often cheaper than resale prices offered on secondary markets. This tendency further complicates the modeling of consumer expectations.

Our paper also differs from the stream of marketing and economic literatures that study resale markets as a competitor to firms' marketing efforts in durable goods categories (Desai and Purohit 1998; Desai et al. 2002; Shulman and Coughlan 2007; Chen, Esteban and Shum. 2013; Hendel and Lizzeri 1999). While the secondary market can provide competition to the team's efforts to sell single game tickets, our emphasis is on retention. We also focus on a service category that involves ongoing relationships with consumers rather than infrequently purchased durables.

2.4 Summary

Season ticket buying entails significant complexity including uncertain product quality, advance buying, bundling, price discounts and options to resell tickets. The extant literature provides insights into how these elements might influence consumer behavior. The season ticket management process is somewhat differentiated by the level of data available post purchase. Sports franchises are increasingly able to observe downstream activities such as usage and reselling. These insights and available data provide the foundation for our model development in Section 4.

3. Data, Model Free Evidence and Reduced Form Analyses

The primary data used in our analysis are transaction histories for season ticket customers of a Major League Baseball team for the seasons from 2011 to 2016. The sample consists of 1,924 customers who purchased season ticket packages at least once between the seasons from 2011 to 2016. Known ticket brokers are not included in the sample. Each customer has a unique account number that allows tracking each customer's season and single game ticket purchases from the team over the 6-year period. For each transaction, we observe the ticket type (quality tier) purchased and the prices paid. The team also tracks ticket usage through bar codes, and is able to monitor attendance and ticket resales conducted via StubHub. The team data contains successful resale information but does not include information on listed tickets that do not sell. We augment the team data with ticket listing data from a data broker by matching seat section, row, and seat number. This provides a complete picture of season ticket holders' game level ticket usage decisions. Specifically, we are able to observe whether a ticket is used for attendance, listed, resold or forgone.

The purchase incidence rate of season tickets for the sample was 66.4% during the 6-year observation window. An important issue in season ticket management and ticket sales is that there is significant heterogeneity in ticket quality within a stadium or arena. The team under study classifies tickets into 6 quality tiers. The average season ticket price per ticket ranged from $54 in the highest quality tier to $8 in the lowest quality tier. It is worth noting that while the use of bar code technology and the observability of the secondary market provide unprecedented levels of ticket usage monitoring, the club’s ability to monitor fan behavior is still imperfect. For example, the team does not know if tickets are given away or sold via private transactions.

In this section, we provide several sets of descriptive data and reduced from analyses that provide insight into season ticket holder behaviors and the team’s pricing policies. The intent of the section is to highlight the relationship between the options afforded by the secondary market activity and customer behaviors such as retention. This material reveals basic patterns of consumer behavior and motivates the structure of our model in the next section. In these analyses we also devote significant attention to segment level differences based on ticket quality preferences. This material highlights important customer management issues faced by the team and highlights the importance of our modeling approach.

3.1 Descriptive Statistics

Tables 1 and 2 illustrate several issues related to consumer demand over time. Table 1 shows the distribution of ticket quality and purchase incidence decisions across seasons. The table is organized around the 6 ticket quality tiers defined by the team. The table shows the proportion of customers purchasing within each of the quality tiers and the percentage that do not buy in a given season. In terms of ticket quality, about 11% of customers purchase in the highest premium tier (Tier 1), while about 6% purchase in the lowest quality level (Tier 6). The most common quality tier for season ticket holders is Tier 2, which accounts for approximately 20% of customers. The proportion of customers not purchasing season ticket packages increased over time, from 26% in the 2011 season to approximately 50% in the 2016 season. This is likely due to the team's declining performance over the 6 years.

Table 2 shows the renewal rates for season ticket buyers conditional on previous seat tier choice. There is a substantial stickiness in the purchase of season tickets. The year-to-year renewal rate of season tickets is over 83% in the highest quality seat tiers (Tier 1-4). Renewal rates for Tiers 5 and 6 are about 75%. There is very little switching across seat tiers.

Table 3 shows data related to pricing and the importance of season ticket sales across sections. The top of Table 3 shows pricing data including average per game season ticket prices and single game ticket prices across tiers. There are several notable features of the pricing schedule. *First*, ticket prices are substantially different across seat tiers. *Second*, season tickets are discounted from 35% to 50% relative to single game tickets, with a smaller discount (35%) for high quality tier tickets and a larger discount (50%) for low quality tier tickets. There is also a much smaller variation in season ticket prices within each category relative to single game prices.

This occurs because the team varies prices of single games based on opponent and factors related to time (weekend, day versus night game).

The bottom of Table 3 shows the percentage of season ticket sales per tier. For the two highest quality seat tiers, 80% to 86% of seats are purchased by season ticket buyers. The percentage of tickets purchased by season ticket holders decreases as seat quality diminishes. For Tier 3 the percentage is 66%, for Tier 4 it is 60% and the percentage is less than 30% for Tiers 5 and 6. The concentration of season ticket purchases in the most expensive blocks of tickets highlights the economic importance of these customers to the team.

3.2 Secondary Market Behaviors and Segment Level Differences

The foundation of our analysis is the idea that the secondary market changes the value proposition of season tickets by providing options to consumers. The most significant option is that season ticket buyers have the option to unbundle ticket packages and recoup costs by selling tickets on the secondary market. In addition, given the significant differences in ticket prices and renewal rates, it may also be critical for the analysis to consider segment level differences. Fans seem to vary both in terms of behaviors and in the value provided to the team. Our goal in this section is to provide data that highlights behaviors related to the options to use versus sell tickets, and data that highlights behavioral and value differences across ticket quality levels.

Table 4 shows data related to consumers' ticket usage alternatives. The top portion of the table shows consumers' "intended" ticket usage as of the day before the start of each game. We infer "intentions" based on whether a ticket is listed prior to a given game. Specifically, if we observe that an individual has listed a ticket on the secondary market before the game we interpret this as an intention to resell rather than attend the game. The attendance and forgo rates reflect the usage decisions for non-listed tickets. There is substantial variation in attending and reselling intentions across seat tiers. Higher quality ticket holders are more likely to plan on game attendance and less likely to list tickets. For example, the intended attendance rates in Tier 1 and 2 are more than 70% while the rate for Tier 6 was only 50%. Resale listing rates tend to grow as ticket quality diminishes. The higher quality tier tickets (e.g. Tier 2) have a listing rate close to 6%, while the lowest quality tier tickets have a 12% listing rate.

Figure 1 plots the intended usage patterns across seasons. An initial observation is that non-usage rates are stable from 2011 to 2014 but significantly increased in 2015 and 2016. Listing rates also declined in 2015 and 2016. This pattern corresponds to the team performance. It appears that as team performance declines, season ticket holders are more likely to plan on skipping games rather than attending or listing on secondary markets.

While we view listing decisions as reflective of consumer plans or intentions, consumers may fail to resell tickets if demand is weak or prices are set too high. If a consumer fails to sell a ticket, then the consumer makes an additional decision of whether or not to attend. The bottom of Table 4 shows reselling success rates for listed tickets across seat tiers. On average, there is a 36% probability that a listed ticket sells on the secondary market. The resale rates in high quality tiers are approximately 10% lower than in low quality tiers (e.g., 30% in Tier 1 versus 40% in Tier 6). There is also variation in the contingency behaviors across different quality tiers when resale attempts fail. When a listing does not sell, there is a 68.4% chance ($\frac{47.83\%}{(47.83\%+22.10\%)}$) that Tier 1 season ticket holders choose to attend the game instead of forgoing the ticket. In contrast, Tier 6 ticket holders have a 33% chance to attend the game.

These differences in reselling and usage, suggest that season ticket holders with different quality ticket preferences differ in their resale motivations. High quality tier holders are less likely to list and more likely to attend when listings fail. These high-tier customers might have higher reservation values and therefore might price tickets higher. This also explains the lower listing frequency. For buyers of lower quality tickets, there seems to be less interest in attending games and greater interest in selling tickets. The "Actual" usage section of Table 4 reports the ultimate ticket usage decisions by seat tier. When comparing "Actual" with "Intended" usage, we can see that the actual resale rates are much lower than the listing rates across all tiers.

Table 5 shows key pricing data including secondary market listing prices and resale transaction prices. List prices tend to be set at values very close to single game ticket prices. The list-to-single price ratio ranges from about 1 for Tier 1 tickets to .84 for Tier 6 tickets. Differences in response to failed reselling attempts may explain the variation in season ticket holders' secondary market pricing decisions. If a customer is more likely to use a ticket that fails to sell, then that customer may be more likely to try for a higher price. Alternatively, tickets may be listed at lower prices if it is an either-resale-or-waste-ticket scenario. The observed data is consistent with our speculation that the 'residual' usage value of an unsuccessful resale could be a driver of the listing prices. Another interesting pattern is that the actual resale prices (from the successful transactions) are lower than the listing prices. Secondary market tickets tend to sell at values between the season ticket and single game prices.

Another important question is whether resale prices and resale probabilities are a function of the aggregate probability of season ticket holders selling their tickets. This is important since increased interest in the secondary market by season ticket holder might impact equilibrium list prices, resale prices, and resale probabilities. Table 6 reports the results of three sets of regressions. In the first column, we run a logistic regression of secondary market ticket resale success as a function of the percentage of season ticket holders listing tickets on the secondary market. We also include the list price ratio (listed prices versus single game prices), seat tier, and game quality measures as control variables. As a proxy for game quality we use the total gate ticket revenues for the game. In the second column, we regress ticket list price ratios on the percentage of season ticket holders listing on the secondary market, game quality and seat tier. The third column reports a regression the predicts resale price ratio using the same set of explanatory variables. Across all the three regressions, we find a significant negative impact of secondary market competition on the dependent variables. This suggests that the overall value provided by the secondary market to season ticket holders may be limited by supply factors. An efficient secondary market attracts more season ticket holders to participate in the market and this pushes down equilibrium prices and resale probabilities.

An open question is whether consumers make ticket usage and selling decisions strategically across groups of games. If this is the case, then it might be necessary to model sequences of ticket usage decisions rather than game level decisions. As a test of whether fans make decisions across sequences of games we estimate a logistic regression of season ticket holder's game level resale listing decision (yes=1, no=0) on the game quality index of the current and the next five games. We again use the individual game ticket sales revenue as an approximation for game quality and include quality tier level fixed effects. We also control for cross-individual variations in individual listing rates, as well as non-usage rates. Table 7 shows that the coefficients of game quality index of the future five games are all non-significant, while the current game quality has a significant positive coefficient. It suggests that season ticket holders are more likely to list the tickets for an attractive game, and that they do not make listing decisions based on future games.

3.3 Customer Retention

The preceding analyses reveal patterns of behavior within seasons. While these analyses highlight the options available to customers and differences in behavior across quality based segments, they do not speak directly to questions of behavior across seasons. Our primary interest is in how consumers make decisions about season ticket purchasing. We next attempt to link these within season ticket usage decisions to the decision to buy a ticket package in the subsequent season.

We begin with data that highlights the substitutability of single game tickets for season ticket packages. Table 8 shows the substitution of single-game for season tickets. The first row of the table reports the number of single game tickets purchased by customers that did not renew season tickets. When customers allow season tickets to lapse, they often continue to attend games. Over the observation period, lapsed season ticket purchasers purchased approximately 14 games directly from the team. Far fewer games are purchased on the secondary market versus directly from the team (.12 versus 14 games). The second row shows single game buying patterns in the year prior to a season ticket purchase. On average, customers that became season ticket buyers purchased 23.48 games in the previous year. The higher single game purchases make sense as these consumers were likely becoming more interested in the team over time. As before, there was very little activity in terms of secondary market purchases as only .23 games were purchased on the secondary market. It appears that the segment of customers interested in season tickets has a strong preference for purchasing from the team whether for season or single game tickets.

These results are important for our subsequent model development. First, the data shows that season ticket packages and single game tickets operate as substitutes. The model must, therefore, consider the option to purchase packages versus collections of single games. Second, for the focal team it does not appear that the secondary market operates as a significant source for game tickets for the segment of consumers under study.

Next, we present a reduced-form analysis that explores the link between individuals' secondary market activity and season ticket renewal decisions. Specifically, we look at whether season ticket holders' renewal rates increase as fans become more successful in reselling tickets on the secondary market. This analysis leverages within-individual, across-season variation in renewal decisions, listing rates, and resale rates. We estimate a panel logistic regression with the following specification:

(1) $Renew_{it} = \beta_{0i} + Season_t\beta_1 + \beta_2 AttdRate_{i,-1} + \beta_3 ListRate_{i,t-1} + \beta_4 ResaleRate_{i,t-1} + \beta_5 ResalePriceRatio_{i,t-1} + \beta_6 ResaleRate_{i,t-1} \times ResalePriceRatio_{i,t-1}$

where $Renew_{it}$ indicates whether customer i purchases a season ticket package in season t, β_{oi} controls for individual random effects, $Season_t$ controls for year fixed effects, $AttdRate_{i,-1}$ is last season's game attendance rates, $ListRate_{i,t-1}$ is last season's ticket listing percentage, $ResaleRate_{i,t-1}$ measures the successful resale rates conditional on listing, and $ResalePriceRatio_{i,t-1}$ measures the average ratio between individual i's resale prices and gate prices in season t-1.

Table 9 shows the panel logistic regression results. The first notable observation is that after controlling for attendance rate, a higher ticket listing percentage is a positive indicator for season ticket renewal. Second, how likely and at what price a listed ticket sells at matters. We find that the effect of successful resale rates is moderated by the resale price. At the average resale price ratio of .62, a one percent increase in resale rates will increase the renewal odds ratio by approximately 1.3%. However, low resale prices can interact negatively with resale rates. In the data, we observe resale prices ratios as low as .11. At that level, a 1% increase in successful resale rates will reduce the renewal odds ratio by 5.8%.

3.4 Data Summary

The preceding descriptive statistics and reduced from analyses reveal important aspects of how a secondary market for tickets influences the behavior of season ticket customers. The data suggests that the secondary market provides a set of options regarding ticket usage. Consumers have options to sell tickets, attend games or discard tickets. These options can also be conditional since some customers exercise the option to attend if a resale attempt fails. We also observe that season packages and single game tickets can serve as substitutes. However, for the team under investigation, far fewer single game tickets are purchased on the secondary market versus directly from the team. These findings suggest that econometric analyses of fan buying behavior should explicitly model the complex set of options available to consumers.

There is also correlational data that greater success in disposing tickets on the secondary market is positively related to renewing. However, this analysis also suggests that if consumers are only able to obtain very low prices then renewal rates suffer. This analysis provides initial evidence of both the importance of the secondary market in providing incremental value to customers and also evidence that supply and demand forces can mitigate the value proposition. Finally, the significant differences in behavior across seat quality tiers highlights the importance of considering observable quality preference heterogeneity when implementing our model.

4. Model

In this section, we develop a structural model of season ticket purchasing, single game buying and game level usage. At the core of our model is the need to incorporate the various consumer options regarding ticket type choice and usage, and the interdependence between resale listing decisions and resale prices on the secondary markets. The overarching logic of the modeling approach is illustrated in Figure 2.

4.1. Usage Decision of Season Tickets

Given the temporal separation of season ticket purchases relative to the actual usage of season tickets, we start by modeling consumer's utility of using each ticket prior to game day. The core of this analysis is the utility of attending a given game. Consumer i's utility from attending game g with a quality tier j season ticket in season t is given as in equation (2):

$$u^{A}_{igt|j} = Q_{igt|j} + \varepsilon^{A}_{igt|j} \tag{2}$$

where $Q_{igt|j}$ indicates consumer $i's$ perceived game quality before the game day and $\varepsilon^{A}_{igt|j}$ is an error term that follows the standard Type-I extreme value distribution. We specify game quality as $Q_{igt|j} = \beta_{1ij} + X_{gt}\beta_{2i} + W_{gt}\beta_{3i} + \xi_{1gt}$. We include three sets of variables to approximate game quality. *First*, β_{1ij} are seat tier preferences, indicating that the perceived game quality varies by seat quality tiers. *Second*, X_{gt} includes the set of game attributes known at the beginning of each season including year fixed effects, game schedule type indicators (weekday, night, holiday), and the opposing team's winning percentage from last season and relative pay rates at the beginning of this season. The home team's quality level is captured through year fixed effects. *Third*, we also include another set of variables W_{gt} that only becomes available as a given game approaches. W_{gt} includes home and oppossing teams' cumulative winning percentage from the beginning of the season to game g, the absolute difference between the home and visiting team's winning percentage (a game competitive balance measure), the home team's current winning or losing streak, and the home team's current divisional standing measured by "games back" from the division leader. We demean the components of W_{gt} so that the variables have zero means. Finally, we also include a game specific unobserved shock term ξ_{1gt}. This term captures game quality factors that are not included in the observed game attributes $\{X_{gt}, W_{gt}\}$, such as competition from other sporting/entertainment events in the city. The realized shock ξ_{1gt} is observed by consumers but not the researchers. Consumer i with a tier j season tickets can also forgo game g. We normalize the mean utility of forgoing a ticket to zero as in equation (3):

(3) $$u_{igt|j}^{F} = \varepsilon_{igt|j}^{F}$$

where the error term $\varepsilon_{igt|j}^{F}$ follows the standard Type-I extreme value distribution.

Next, we model the utility of listing a ticket for resale. We model listings rather than resale transactions, because not all listings lead to successful transactions. The utility of listing is the cost associated with listing on the secondary market plus a weighted average of revenues from a successful resale and the maximum value of attending or forgoing a game when a resale attempt fails. This utility is given in equation (4):

(4) $$u_{igt|j}^{L} = -c_i + q_{jgt}(r_i) \cdot \left(\delta\beta_{4i} \cdot r_i \cdot GateP_{jgt} + \varepsilon_{ijgt}^{L}\right) + \left(1 - q_{jgt}(r_i)\right) \cdot \max\left\{u_{igt|j}^{A}, u_{igt|j}^{F}\right\}$$

In this equation c_i represents the costs (time and effort) incurred by consumer i when listing a ticket on the secondary market. The second component represents the utility from a successful resale, where q_{jgt} is the probability of a successful sale, and the expression in the parentheses is the revenue gain from the sale. The δ term captures the commission charged by the secondary market platform. We set δ to .90, as StubHub charges a 10 percent commission rate for sellers.[1] Parameter β_{4i} is a price coefficient that captures the marginal utility from a dollar gain for the consumer. This specification allows us to measure each seller's listing cost in dollar form as $\frac{c_i}{\beta_{4i}}$. We normalize the list prices by the tier-specific gate prices. The term r_i is the ratio of list prices relative to gate price. We also include an error term ε_{ijgt}^{L} to reflect the unobserved utility from a successful resale (e.g. transaction utility). The last component of the equation reflects the utility

[1] StubHub charges 10 percent from sellers and another 25 percent commission from buyers. For example, if the listing price is \$100. Sellers get \$90 out of \$100, and buyers pay \$125. StubHub makes \$35 out of the transaction.

associated with a failed resale attempt. When a season ticket holder cannot resell a ticket, he or she can still obtain utility by either attending a game or forgoing use of a ticket.

The utility of listing can be viewed from a probabilistic perspective. We illustrate the rationale behind resale attempts with two extreme scenarios. In the case that a listed ticket k has a zero percent chance to be sold on the secondary market ($q_{k,jgt} = 0$), and consumer i has a schedule conflict where $\max\{u^A_{igt|j}, u^F_{igt|j}\} = u^F_{igt|j}$, then no attempt at resale should be made as $u^L_{igt|j} = -c_i + u^F_{igt|j} < u^F_{igt|j}$. In contrast, if a listed ticket k can be sold for certainty ($q_{k,jgt} = 1$), then the ticket should be listed as long as the revenue gain $\delta\beta_{3i} \cdot r_i \cdot GateP_{jgt}$ exceeds the listing cost c_i.

4.2. Resale Probability

We model secondary market demand through the resale probability $q_{k,jgt}$ of each listed ticket k of tier quality j for game g in season t using an aggregate logit form as in equation (5):[2]

$$q_{k,jgt} = \frac{exp(\gamma_{1j}+\gamma_2 A_{jgt}+\gamma_3 L_{jgt}-\gamma_4 r_{k,jgt}+\xi_{2gt})}{1+exp(\gamma_{1j}+\gamma_2 A_{jgt}+\gamma_3 L_{jgt}-\gamma_4 r_{k,jgt}+\xi_{2gt})} \quad (5)$$

where γ_{1j} are tier specific intercepts, term A_{jgt} represents perceived game quality for game g in tier j for an average fan, term $L_{jgt}$is the observed percentage of season tickets listed on secondary markets and term $r_{k,jgt}$ is the ratio of secondary market price relative to gate price. Coefficient γ_4 measures secondary market buyers' price sensitivity .

We specify the perceived game quality of an average secondary market ticket buyer as $A_{jgt} = \bar{\beta}_{1j} + X_{gt}\bar{\beta}_2 + W_{gt}\bar{\beta}_3$. The game quality has the information available prior to the season X_{gt} and the team and opponent performance data W_{gt} revealed as a season progresses. We use the

[2] We use an aggregate logit form to model the resale probability of each listed ticket, as we do not have panel data of the secondary ticket purchase.

average preference parameters to approximate the quality perception of an average fan. We also include an unobserved secondary market demand shock ξ_{2gt}, and allow a covariance structure between ξ_{1gt} and ξ_{2gt} where $\xi_{gt} \sim N(0, \Sigma_{\xi})$. We allow correlation because the same unobserved factor could drive season ticket holders' attendance and secondary market demand for the game (i.e. competition from other entertainment events, or a heralded high flying rookie in a game).

For simplicity, we denote $a_{jgt} = \gamma_{1j} + \gamma_2 A_{jgt} + \gamma_3 L_{jgt}$, and write the probability as:

(6) $$q_{k,jgt} = \frac{exp(a_{jgt} - \gamma_4 r_{k,jgt})}{1 + exp(a_{jgt} - \gamma_4 r_{k,jgt})}.$$

4.3. Secondary Marketing Listing Prices

A critical component of the model is the customer's decision of the listing price when selling on the secondary market. Given the tradeoff between recouping costs, making a sale, and the utility of attending or forgoing following a failed resale, each customer decides on a game specific list price ratio r^* (price relative to gate prices) that maximizes utility. An expression for a consumer's optimal list price ratio r_i can be determined by taking the first-order condition of equation (4). Dropping the subscript jgt for simplicity, the optimal list price ratio is written in equation (7)

(7) $$r_i^* = \frac{\max\{u_i^A, u_i^F\} - \varepsilon_i^L}{\delta \times \beta_{4i} \times GateP} + \frac{q(r_i^*)}{|\partial q(r_i^*)/\partial r_i|}.$$

Depending on the shape of secondary market demand curve $q(r_i^*)$, there is a shared level of the optimal list price ratio $\frac{q(r_i^*)}{|\partial q(r_i^*)/\partial r_i|}$. However, every individual will have a different markup $\frac{\max\{u_i^A, u_i^F\} - \varepsilon_i^L}{\delta \times \beta_{4i} \times GateP}$, as he or she has a different utility of attending or forgoing a game. This feature of the first order condition explains why conditional on seat tier and game attributes there is still a distribution of list prices. As illustrated in Table 5, the distribution of list price ratios is partially a reflection of the value of contingency plans to either attend or forgo a game when a listing fails.

If we insert the resale probability $q_{k,jgt}$ from equation (6) into equation (7), absorb jgt, we obtain a closed-form expression for the optimal list price ratio (see Appendix A for details):

$$(8) \qquad r_i^* = \frac{a - \ln t_i + W(t_i)}{\gamma_4}$$

where $t_i = exp\left(a - \gamma_4 \times \frac{\max\{u_i^A, u_i^F\} - \varepsilon_i^L}{\delta \times \beta_{4i} \times GateP} - 1\right)$ and W(.) is the Lambert-W (or omega) function. The expression suggests that the optimal list price ratio is determined by the contingency value of attending or forgoing a game $\max\{u_i^A, u_i^F\}$, the season ticket holder's price coefficient β_{4i}, secondary market demand parameters a, and the secondary market price coefficient γ_4.

4.4. The Probability of Listing Season Tickets to Resell

Season ticket holders will list a ticket on secondary markets if the utility of listing is larger than the maximum utility from either attending or forgoing a ticket. This can be represented as $Pr\left[u_i^L \geq \max\{u_i^A, u_i^F\}\right]$ in probability terms. Expanding the expression for u_i^L, we can write the condition as:

$$(9) \; Pr\left[-c_i + q(r_i) \cdot (\delta\beta_{4i} \cdot r_i \cdot GateP + \varepsilon_i^L) + \left(1 - q(r_i)\right) \cdot \max\{u_i^A, u_i^F\} \geq \max\{u_i^A, u_i^F\}\right]$$

We can then insert the optimal list price ratio r_i^* (equation 8) to obtain the following expression (see Appendix B for details):

$$(10) \qquad Pr\left[\frac{\delta\beta_{4i} \cdot GateP}{\gamma_4}\left(a - 1 - \ln\frac{\gamma_4 c_i}{\delta\beta_{4i} \cdot GateP}\right) - c_i + \varepsilon_i^L \geq \max\{u_i^A, u_i^F\}\right]$$

Given both the error terms in the attendance and forgo utility specifications follow the standard Type-I extreme value distributions, we can express the distribution of the maximum of the two as $\max\{u_i^A, u_i^F\} = v_i^{AF} + \varepsilon_i^{AF}$, where $v_i^{AF} = \exp\left(Q_{igt|j}\right) + 1.0$ and ε_i^{AF} also follows the standard Type-I extreme value distribution. Given that both ε_i^{AF} and ε_i^L are distributed as standard Type-I extreme value, we can derive the probability of listing a season ticket to resell as:

(11) $$Pr\left[u_i^L \geq \max\{u_i^A, u_i^F\}\right] = \frac{exp(\phi_i^L)}{exp(\phi_i^L)+exp(v_i^{AF})}$$

where

(12) $$\phi_{igt|j}^L = \frac{\delta\beta_{4i}\cdot GateP}{\gamma_4}\left(a - 1 - \ln\frac{\gamma_4 c_i}{\delta\beta_{4i}\cdot GateP}\right) - c_i.$$

Equations (11) and (12) show that the probability of listing a season ticket to resell is a function of secondary market demand parameters a and γ_4, as well as the season ticket holder's price coefficient β_{4i} and listing cost c_i. This allows for more resale listings as a season ticket holder's price coefficient β_{4i} increases. Alternatively, the probability of listing will decrease if the listing cost c_i increases or if secondary market buyers become more price sensitive γ_4. The inclusion of this supply and demand structure is particularly relevant for counterfactual analyses related to minimum or maximum pricing policies.

4.5. Season Ticket Purchase

We now model the season ticket purchase decision. This decision is made prior to the start of the season. This introduces significant uncertainty as consumers can only make probabilistic judgments about team quality over the 81 game season. Our assumption is that consumers have rational expectations of game quality based on information $\{X_{gt}\}$ available before the start of the season. The expected game quality before the start of a season takes the form $\mathrm{E}(Q_{igt|j}) = \beta_{1ij} + X_{gt}\beta_{2i}$ where X_{gt} includes the set of game attributes known at the beginning of each season including year fixed effects, game schedule type indicators (weekday, night, holiday), and the opposing team's winning percentage from last season and relative pay rates at the beginning of this season.

In contrast to the usage decision information set, the terms for within season data W_{gt} and ξ_{1gt} are not included. W_{gt} contains information not available at the time of season ticket purchase such as the home team's divisional standing before game g. An important implication of our specification of game quality is that the expected quality of a game at the time of season ticket purchase may deviate from the revealed game quality at the time of ticket usage decisions (game day). The discounts provided for season ticket packages may be viewed as compensation for the consumer's pre-commitment for this uncertainty.

The decision to purchase a season ticket package or not depends on the sum of the expected usage utility of the 81 games $\sum_{g=1}^{81} USE_{igt|j}$ in an MLB home season. The expected usage utility of any single game is a function of the three usage options, to attend, forgo, or to list a ticket to resell. Before the start of a season, consumers only have the information in $\{X_{gt}\}$ to inform their season ticket purchase decision. We replace the game quality perception $Q_{igt|j}$ with $\mathrm{E}\left(Q_{igt|j}\right)$ in equation (2) and denote the expected game attendance utility before the start of a season as $\tilde{u}_{igt|j}^{A} = \mathrm{E}\left(Q_{igt|j}\right) + \tilde{\varepsilon}_{igt|j}^{A}$. Similarly, we also replace the secondary market game quality perception A_{jgt} with $\mathrm{E}\left(A_{jgt}\right)$ in equation (5) and denote the expected ticket listing utility before the start of a season as $\tilde{u}_{igt|j}^{L} = -c_i + \tilde{q}_{jgt} \cdot \left(\delta\beta_{4i} \cdot r_i \cdot GateP_{jgt} + \tilde{\varepsilon}_{ijgt}^{L}\right) + \left(1 - \tilde{q}_{jgt}\right) \cdot \max\{\tilde{u}_{igt|j}^{A}, \tilde{u}_{igt|j}^{F}\}$.

The expected overall usage utility for game g is the weighted average of the expected utility of attending game or forgoing a ticket, $\max\{\tilde{u}_i^A, \tilde{u}_i^F\}$, and the expected listing utility $\tilde{u}_i^L$, with the corresponding weights equal to $Pr\left[\max\{\tilde{u}_i^A, \tilde{u}_i^F\} \geq \tilde{u}_i^L\right]$ and $Pr\left[\tilde{u}_i^L \geq \max\{\tilde{u}_i^A, \tilde{u}_i^F\}\right]$, respectively. We express the expected usage utility, $USE_{igt|j}$, of a season ticket for game g, in tier j in season t for consumer i as (subscripts jgt suppressed for simplicity):

(13) $$USE_i = Pr\left[\max\{\tilde{u}_i^A, \tilde{u}_i^F\} \geq \tilde{u}_i^L\right] \cdot \max\{\tilde{u}_i^A, \tilde{u}_i^F\} + Pr\left[\tilde{u}_i^L \geq \max\{\tilde{u}_i^A, \tilde{u}_i^F\}\right] \cdot \tilde{u}_i^L$$

Given that $\max\{\tilde{u}_i^A, \tilde{u}_i^F\} = \tilde{v}_i^{AF} + \tilde{\varepsilon}_i^{AF}$, $\tilde{u}_i^L = \tilde{v}_i^L + \tilde{\varepsilon}_i^L$ and the error terms of $\tilde{\varepsilon}_i^{AF}$ and $\tilde{\varepsilon}_i^L$ are Type-I extreme value distributed we can rewrite the expression for USE_i as in equation (14).

$$(14) \qquad USE_i = \int_{-\infty}^{\infty}\int_{\tilde{v}_i^L-\tilde{v}_i^{AF}+\tilde{\varepsilon}_i^L}^{\infty}\left(\tilde{v}_i^{AF}+\tilde{\varepsilon}_i^{AF}\right)dF\left(\tilde{\varepsilon}_i^{AF}\right)dF(\tilde{\varepsilon}_i^L) + \int_{-\infty}^{\infty}\int_{-\infty}^{\tilde{v}_i^L-\tilde{v}_i^{AF}+\tilde{\varepsilon}_i^L} -c + \tilde{q}(r^*)(\delta\beta_4 \cdot r \cdot GateP + \tilde{\varepsilon}_i^L) + \left(1-\tilde{q}(r^*)\right)\left(\tilde{v}_i^{AF}+\varepsilon_i^{AF}\right)dF\left(\tilde{\varepsilon}_i^{AF}\right)dF(\tilde{\varepsilon}_i^L).$$

We show more details on the integration of equation (14) in Appendix C. Given the expected usage utility $USE_{igt|j}$, we can write consumer i's utility from buying a season ticket as:

$$(15) \qquad u_{ijt}^S = k_{it} + \tau_i \sum_{g=1}^{81} USE_{igt|j} - \tau_i\beta_{4i}SeasonP_{jt} + \varepsilon_{igt}^S$$

where $SeasonP_{jt}$ refers to the season ticket price for a particular seat tier j in season t. $SeasonP_{jt}$ shares the same price coefficient β_{4i} as the resale revenue in equation (4) as we assume the value of a dollar spent is the same as a dollar collected in the secondary market. We also include a scale parameter τ_i for $\sum_{g=1}^{81} USE_{igt|j}$ and $\beta_{4i}SeasonP_{jt}$, as they involve a summation over 81 games and are on a different scale from the additive unobserved term ε_{igt}^S. Intercept k_{it} captures the intrinsic value of buying a season ticket as opposed to the no-purchase option.

4.6. Single Game Purchase

The model-free evidence suggests that a collection of single gate tickets represent a substitute for season ticket package. Rather than normalize the no-purchase option ($j = 0$) to zero, we allow the utility of not purchasing season tickets to be a function of consumers selectively buying single tickets for a subset of games. The utility of buying a tier j gate ticket to game g in season t follows as:

$$(16) \qquad u_{ijgt}^G = \beta_{5i} + Q_{igt} - \beta_{4i}GateP_{jgt} + \varepsilon_{ijgt}^G$$

The game quality measure at the time of buying a gate ticket has the same specification as that in the season ticket usage decision in equation (2), as consumers have more revealed game quality information at that time. Another difference is that gate tickets sell at higher prices compared to season tickets. Because the team sets individual game prices based on timing factors and opponent attractiveness, season tickets are sold at a discount of between 30% to 50% discounts depending on the tier. We also include a single gate ticket intercept to indicate the preference of purchasing a gate ticket for game g. We normalize the mean utility of the outside option of not purchasing a ticket for game g to zero $u_{i0gt}^{G} = \varepsilon_{i0gt}^{G}$.

Next, we model the expected utility of waiting to buy single game gate tickets for any subset of the 81 games at the time of season ticket purchase. Similar to the season ticket purchase in Section 4.5, consumers do not have information on $\{W_{gt}\}$ at the time of forgoing season ticket packages. Thus, we replace the game quality perception $Q_{igt|j}$ with $\mathrm{E}(Q_{igt|j}) = \beta_{1ij} + X_{gt}\beta_{2i}$ and write the expected utility of waiting to buy single gate tickets as $\sum_g \ln\left[\sum_{j=1}^{6} exp\left(\tilde{v}_{ijgt}^{G}\right) + 1\right] + \lambda$, where $\tilde{v}_{ijgt}^{G} = \beta_{5i} + \mathrm{E}(Q_{igt|j}) - \beta_{4i} GateP_{jgt}$ is the expected utility of buying a single gate ticket at the season ticket purchase stage.Term λ is Euler's constant; we scale the inclusive value by τ_i. The utility of not buying a season ticket is therefore:

$$u_{i0t}^{S} = \tau_i\left(\sum_g \ln\left[\sum_{j=1}^{6} exp\left(\tilde{v}_{ijgt}^{G}\right) + 1\right] + \lambda\right) + \varepsilon_{i0t}^{S} \tag{17}$$

4.7. Heterogeneity

We model consumer heterogeneity using a hierarchical structure. We use $\theta_i = (\beta_i, c_i, k_i, \tau_i)'$ to indicate the set of parameters that vary across individuals. We include both observed and unobserved individual heterogeneity as below:

$$\theta_i = \bar{\theta} + \Pi D_i + \Sigma v_i \tag{18}$$

where D_i is a vector of observed demographics including individual's tenure in years with the team, distance to the home stadium, and the median household income in individual's zip codes. Σ is the variance-covariance matrix of the unobserved heterogeneity. Our secondary market sales data is not in a panel format. Therefore, the secondary market demand parameter γ is not estimated at the individual level.

4.8. Likelihood

We let $\mathcal{L}_{it}\left(d_{it}, d_{igt} | \Psi, \beta_i, \gamma, c_i, k_i, \tau_i\right)$ be the likelihood of observing consumer i making season ticket purchase choice $d_{it} = \left\{d_{ijt}^S\right\}$ for season t, and ticket usage and gate ticket purchase decisions $d_{igt} = \left\{d_{igt|j}^A, d_{igt|j}^F, d_{igt|j}^L, d_{ijgt}^G\right\}$ for each game g in season t, conditional on observed variables $\Psi = \{X, W, SeasonP, GateP\}$. This forms the likelihood of any given path of ticket purchase and usage choices in season t:

$$(19) \qquad \mathcal{L}_{it}\left(d_{it}, d_{igt} | \Psi, \beta_i, \gamma, c_i, k_i, \tau_i\right) \equiv \prod_{j=1}^{6}\left[P_{ijt}^S \times \prod_{g}^{81}\left(P_{igt|j}^A\right)^{d_{igt|j}^A} \times \left(P_{igt|j}^F\right)^{d_{igt|j}^F} \times \left(P_{igt|j}^L\right)^{d_{igt|j}^L}\right]^{d_{igt}^S} \times \left[P_{iot}^S \times \prod_{g=1}^{81}\prod_{j=0}^{6}\left(P_{ijgt}^G\right)^{d_{ijgt}^G}\right]^{d_{iot}^S}$$

We assume the errors ε in Equation (2), (3), and (4) follow standard Type-I extreme value distributions. In all the equations below, we use v to denote the corresponding deterministic part in each of the utility functions specified above. We can write the probability of a consumer buying a tier j season ticket as:

$$(20) \qquad P_{ijt}^S = \frac{exp\left(v_{ijt}^S\right)}{\sum_{k=1}^{6} exp\left(v_{ikt}^S\right) + exp\left(v_{iot}^S\right)}$$

Similarly, the probability of a consumer not buying a season ticket is:

$$(21) \qquad P_{i0t}^S = \frac{exp\left(v_{i0t}^S\right)}{\sum_{k=1}^{6} exp\left(v_{ikt}^S\right) + exp\left(v_{i0t}^S\right)}$$

The probability of a consumer choosing to attend with, forgo, or list a game g ticket conditional on having purchased a tier j season ticket are given, respectively, in equations (22), (23) and (24).

$$(22) \qquad P_{igt|j}^A = \frac{exp\left(v_{igt|j}^A\right)}{exp\left(v_{igt|j}^A\right) + exp\left(v_{igt|j}^F\right) + exp\left(\varphi_{igt|j}^L\right)}$$

and

(23) $$P^F_{igt|j} = \frac{exp\left(v^F_{igt|j}\right)}{exp\left(v^A_{igt|j}\right)+exp\left(v^F_{igt|j}\right)+exp\left(\varphi^L_{igt|j}\right)}$$

and

(24) $$P^L_{igt|j} = \frac{exp\left(v^L_{igt|j}\right)}{exp\left(v^A_{igt|j}\right)+exp\left(v^F_{igt|j}\right)+exp\left(\phi^L_{igt|j}\right)}.$$

Alternatively, the probability of a consumer choosing to buy a gate ticket for game g conditional on *not* purchasing tier j season tickets is:

(25) $$P^G_{ijgt} = \frac{exp\left(v^G_{ijgt}\right)}{\sum_{k=1}^{6} exp\left(v^G_{ikgt}\right)+exp\left(v^G_{i0gt}\right)}.$$

We let $\mathcal{L}_{igt}\left(r_{igt}|d^L_{igt},\Psi,\beta_i,\gamma\right)$ be the likelihood of observing consumer i listing a game g season ticket at a price ratio r_{igt} on the secondary market. We know that $\Delta\varepsilon_i = \varepsilon^{AF}_i - \varepsilon^L_i$ follows a standard Type-I extreme value distribution. By applying the rule of change of variables, we have (see appendix D):

(26) $$\mathcal{L}_{igt}\left(r_{igt}|d^L_{igt},\Psi,\beta_i,\gamma\right) = \left\|\frac{\partial\Delta\varepsilon_{igt}}{\partial r_{igt}}\right\| g\left(\Delta\varepsilon_{igt}\right) = \delta\beta_{3i}\cdot GateP_{gt}\cdot\left[1+exp\left(a_i-\gamma_4 r_{igt}\right)\right]\cdot\frac{exp\left(\Delta\varepsilon_{igt}\right)}{exp\left(1+\left(\Delta\varepsilon_{igt}\right)\right)^2}$$

Taking the product over all games in season t yields equation (26):

(27) $$\mathcal{L}_{it}\left(r_{igt}|d^L_{igt},\Psi,\beta_i,\gamma\right) = \prod_{g=1}^{81}\mathcal{L}_{igt}\left(r_{igt}|d^L_{igt},\Psi,\beta_i,\gamma\right).$$

Next, we denote $\mathcal{L}_{kgt}\left(q_{kgt}|\Psi,\beta_i,\gamma\right)$to be the likelihood of a listed ticket k being sold on a secondary market for game g in season t.

(28) $$\mathcal{L}_t\left(q_{kgt}|\Psi,\beta_i,\gamma\right) = \prod_{g=1}^{81}\prod_{k=1}^{K}\frac{exp(\gamma_{1j}+\gamma_2 A_{jgt}+\gamma_3 L_{jgt}-\gamma_4 r_{k,jgt})}{1+exp(\gamma_{1j}+\gamma_2 A_{jgt}+\gamma_3 L_{jgt}-\gamma_4 r_{k,jgt})}$$

Finally, the three likelihood elements combine to form the overall likelihood over T seasons:

(29) $$\mathcal{LL}\left(d_{it},d_{igt},r_{igt},q_{kgt}\right) = \sum_{t=1}^{T}\sum_{i=1}^{I}\ln\mathcal{L}_{it}\left(d_{it},d_{igt}\right) + \sum_{t=1}^{T}\sum_{i=1}^{I}\ln\mathcal{L}_{it}\left(r_{igt}\right) + \sum_{t=1}^{T}\mathcal{L}_t\left(q_{kgt}\right)$$

5. Estimation

This section describes the identification strategy, endogeneity treatments, and estimation algorithm for the model detailed above. The data required to estimate the model consists of each consumer's season ticket purchase choice $d_{it} = \{d_{ijt}^{S}\}$, ticket usage and gate ticket purchase decisions $d_{igt} = \{d_{igt|j}^{A}, d_{igt|j}^{F}, d_{igt|j}^{L}, d_{ijgt}^{G}\}$, price ratio of each ticket listed for resale relative to the gate ticket prices $\{r_{igt}\}$, resale transaction records of listed resale tickets $\{q_{kgt}\}$, observed variables $\Psi = \{X, W, SeasonP, GateP\}$, and individual specific demographics D_i.

5.1. Identification

We now offer an explanation of how the data identifies the model's parameters. The unknown parameters in the model include $\{\beta_{1ij}, \beta_{2i}, \beta_{3i}, \beta_{4i}, \beta_{5i}, c_i, k_i, \tau_i, \gamma_1, \gamma_2, \gamma_3, \gamma_4\}$ where $\beta_{1ij}, \beta_{2i}, \beta_{3i}$ are the coefficients of game attributes, β_{4i} is the coefficient of price, β_{5i} is the gate ticket intercept compared to an outside option, c_i is the listing cost, k_i is the intercept in the season ticket purchase equation, τ_i is a scale parameter, and $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ are market-level demand parameters for the secondary market. Specifically, γ_4 is the price coefficient parameter for resale tickets on the secondary market.

Parameters $\beta_{1ij}, \beta_{2i}, \beta_{3i}$ are identified by the frequency at which season or gate tickets are attended across different games or tiers. The observed pattern of higher or lower attendance rates of tier j tickets informs tier-specific intercepts, β_{1ij}. The shape of the relationship between the game level descriptive X variables (i.e. weekends, year fixed effects) and attendance rates influences the estimates of β_{2i}. Similarly, the shape of the relationship between the W variables (i.e. game competitiveness before the start of game g) and demand for single gate tickets influences the estimates of β_{3i}. Note that W_{gt} provides exclusion restrictions that allow for the separate identification of single game and season ticket utility functions.

Each individual's price coefficient β_{4i} is identified by the price variation of gate tickets across tiers, games and seasons. As gate ticket prices vary across tiers, games or seasons, a more price sensitive individual is less likely to purchase a high price single game ticket. The single game gate ticket intercept β_{5i} is identified by the frequency at which gate tickets are purchased as compared to the outside option of no purchase when the consumer does not purchase season tickets.

Market level parameters γ in the resale equation are identified by the frequency at which listed resale tickets are sold on secondary markets across games, tiers and seasons. The higher the percentage of resale transactions in a tier, the larger the tier intercept γ_{1j}. Conditional on game attributes and the associated coefficients $\{\beta_{1ij}, \beta_{2i}, \beta_{3i}\}$, we can determine the average game quality measure A_{jgt} used in the secondary market equation. The shape of the relationship between the average game quality measure A_{jgt} and the successful resale rates identifies the coefficient γ_2. Similarly, the shape of the relationship between listed ticket volumes and resale success rates identifies the coefficient γ_3, while the shape of the relationship between the relative list price ratio r_{igt} and resale success rates influences the secondary market price coefficient γ_4.

Identification of the individual level listing costs, c_i, is driven by season ticket holder's relative propensity to attempt to resell a ticket. As noted above, we can identify the market level demand parameters γ, and thus determine $q(r_i)$. We identify individual listing costs through differences in listing rates. Specifically, conditional on the same resale probability, $q(r_i)$, for consumers with similar price coefficients β_{4i} and utility of attending u_i^A we use differences in listing rates to identify listing costs c_i. Through this type of conditional comparison we infer whether lower frequency of listing is due to a high listing cost c_i or due to higher utility of game attendance u_i^A or due to a lower price coefficient β_{4i}.

Conditional on the identification of the parameters related to ticket usage, we can determine the expected usage utility $USE_{igt|j}$ of a season ticket game g. Given the expected usage utility, the season ticket purchase intercept k_i is identified by season ticket purchase rates across individuals over seasons, while the scale parameter τ_i is identified by the error term variance in season ticket purchases.

5.2. Endogeneity of List Prices

An endogeneity issue arises as our model simultaneously includes ticket supply (equations 4 and 7) and aggregate demand (equation 5) in the secondary market. Furthermore, both list prices and resale probabilities are driven by secondary market demand shocks ξ_{2gt}, as the resale probability q enters both listing probability and optimal list prices. Therefore, without correction for endogeneity, the price coefficient γ_4 and ticket supply coefficient γ_3 in the secondary market demand would be biased.

We use two approaches to deal with this endogeneity issue. First, we apply a data augmentation approach in the MCMC Bayesian estimation (Yang, Chen and Allenby 2003). We treat the realizations of secondary market demand shocks ξ_{2gt} as augmented latent variables (to be drawn from the MCMC process). Conditional on the augmented demand shocks ξ_{2gt}, we control for the source of endogeneity. For example, if a particular game has a positive secondary market shock (i.e. more demand and higher resell rates), this would increase the average listing probability as well as the list prices. Such a positive market shock could be inferred from the observed supply side decisions as formulated in equations (4) and (7). The augmentation approach controls for the demand shocks and corrects for the biased price coefficients.

We also apply exclusion restrictions to alleviate concerns related to the simultaneity between the ticket supply equations and aggregate demand equation. First, season ticket holders' price coefficients β_{4i} enter both the listing probability (eq 4) and list price equation (eq 7), but not the aggregate secondary demand expression (eq 5). This creates an exclusion restriction for the secondary market demand equation. Second, individual listing cost, c_i, only enters the listing probability (eq 4) but not the list price (eq 7) or aggregate demand (eq 5). This creates an exclusion restriction for both the list price equation and the aggregate market demand. Because we use a hierarchical specification, the listing cost c_i is a function of the observed demographic variables, in particular, it is a function of the season ticket holder's distance from the stadium (Sweeting 2012). These exclusion variables shift the supply of listed tickets but do not affect secondary market demand. Lastly, others' list prices do not enter season ticket holder i's listing decision. This provides as an exclusion restriction for the listing probability equation (4).

5.3. Estimation Steps

We have three sets of parameters $\theta_i = (\beta_i, c_i, k_i, \tau_i)'$, γ, and $\xi_{gt} = (\xi_{1gt}, \xi_{2gt})$, where θ_i includes individual specific parameters that enter consumer i's purchase and usage decisions and γ includes the market-level demand parameters of the secondary market. Given that our secondary market sales data is not in a panel format, γ is not estimated at the individual level. The ξ_{gt} terms include the market shock ξ_{1gt} to season ticket holders, and the market shock ξ_{2gt} in the secondary market. We allow the two shocks to be correlated, as common unobserved factors could drive the shocks. We now outline the steps in our MCMC estimation.

Step 1. At iteration *m*, given θ_i^{m-1}, we draw γ^{*m} from a random walk $N\left(\gamma^{m-1}, \Sigma_\gamma\right)$ and specify a diffuse prior $\pi_\gamma \sim N\left(0, V_\gamma\right)$. We accept γ^{*m} with probability λ_γ:

$$\lambda_\gamma = min\left\{\frac{\pi\left(\gamma^{*m}, V_\gamma\right)\prod_t \mathcal{L}_t\left(q_{kgt}|\theta_i^{m-1}, \gamma^{*m}, \xi_{gt}^{m-1}\right)\prod_t \mathcal{L}_{it}\left(d_{it}, d_{igt}|\theta_i^{m-1}, \gamma^{*m}, \xi_{gt}^{m-1}\right)\mathcal{L}_{it}\left(r_{igt}|\theta_i^{m-1}, \gamma^{*m}, \xi_{gt}^{m-1}\right)}{\pi\left(\gamma^{m-1}, V_\gamma\right)\prod_t \mathcal{L}_t\left(q_{kgt}|\theta_i^{m-1}, \gamma^{m-1}, \xi_{gt}^{m-1}\right)\prod_t \mathcal{L}_{it}\left(d_{it}, d_{igt}|\theta_i^{m-1}, \gamma^{m-1}, \xi_{gt}^{m-1}\right)\mathcal{L}_{it}\left(r_{igt}|\theta_i^{m-1}, \gamma^{m-1}, \xi_{gt}^{m-1}\right)}, 1\right\}$$

Step 2. We draw ξ_{gt}^{*m} from a random walk $N\left(\xi_{gt}^{m-1}, \Sigma_{\xi}\right)$ and specify a diffuse prior $\pi_{\xi} \sim N\left(0, V_{\xi}\right)$. We accept ξ_{gt}^{*m} with probability λ_{ξ}:

$$\lambda_{\xi} = min\left\{\frac{\pi\left(\xi^{*m}, V_{\xi}\right)\prod_{t}\mathcal{L}_{t}\left(q_{kgt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{*m}\right)\prod_{t}\mathcal{L}_{it}\left(d_{it}, d_{igt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{*m}\right)\mathcal{L}_{it}\left(r_{igt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{*m}\right)}{\pi\left(\xi^{m-1}, V_{\xi}\right)\prod_{t}\mathcal{L}_{t}\left(q_{kgt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{m-1}\right)\prod_{t}\mathcal{L}_{it}\left(d_{it}, d_{igt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{m-1}\right)\mathcal{L}_{it}\left(r_{igt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{m-1}\right)}, 1\right\}$$

We also update the variance-covariance matrix Σ_{ξ} by assuming an inverse Wishart prior distribution $\Sigma_{\xi} \sim IW\left(v_{0}, V_{\xi 0}\right)$.

Step 3. We update the hyper-parameters that govern the distribution of $\theta_{i} \sim N(\Pi D_{i}, \Sigma_{\theta})$. Z_{i} includes customer i's distance to the stadium, years since the first purchase of season tickets, and the matched zip-code level income. We specify the priors to be $\Pi|\Sigma_{\theta} \sim N\left(0, \Sigma_{\theta} \otimes A_{\theta}^{-1}\right)$ and $\Sigma_{\theta} \sim IW(v_{0}, V_{\theta 0})$. Given θ_{i}^{*m} and priors on Π, Σ_{θ}, we draw $\Pi^{m-1}, \Sigma_{\theta}^{m-1}$ from the posterior distributions as we do in the multivariate Bayesian regression setting.

Step 4. In this block of the estimation we update parameters for each individual. We draw θ_{i}^{*m} from a random walk $N\left(\theta_{i}^{m-1}, \Sigma_{\theta}^{m-1}\right)$. The specification implies that $N\left(\Pi^{m-1}D_{i}, \Sigma_{\theta}^{m-1}\right)$ is effectively the prior for θ_{i}^{*m}. Therefore, we accept θ_{i}^{*m} with probability λ_{θ}:

$$\lambda_{\theta} = min\left\{\frac{\pi\left(\theta^{*m};\ \Pi^{m-1}D_{i}, \Sigma_{\theta}^{m-1}\right)\prod_{t}\mathcal{L}_{it}\left(d_{it}, d_{igt}|\theta_{i}^{*m}, \gamma^{m}, \xi_{gt}^{m}\right)\mathcal{L}_{it}\left(r_{igt}|\theta_{i}^{*m}, \gamma^{m}, \xi_{gt}^{m}\right)}{\pi\left(\theta^{m-1};\ \Pi^{m-1}D_{i}, \Sigma_{\theta}^{m-1}\right)\prod_{t}\mathcal{L}_{it}\left(d_{it}, d_{igt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{m}\right)\mathcal{L}_{it}\left(r_{igt}|\theta_{i}^{m-1}, \gamma^{m}, \xi_{gt}^{m}\right)}, 1\right\}$$

6. Results

We ran a total of 50,000 MCMC iterations and report the posterior distributions of the parameters based on the last 20,000 iterations. The model has an 89.46% hit rate for the season ticket purchase decisions. Table 10 shows that the hit rates of season ticket tier choices range from 80% to 93%. We present the estimation results in Table 11.

The first two blocks of results report the estimates for ticket attendance usage in equations (2) and (16). There are several things worth noting. *First*, the magnitudes of the tier dummy coefficients are consistent with the order of the tier choice percentage of season tickets in Table 1. Also, the year dummy coefficients indicate a decline in season ticket purchase rates in Seasons 2015 and 2016, consistent with declining team performance in the two years. *Second*, fans are more likely to attend games at convenient times such as at night or on weekends. In terms of the other game quality information, $\{X_{gt}\}$, available before the start of a season, we find a largely intuitive pattern of results. The visiting team's winning percentage last season and relative pay rates in this season are both significant drivers of attendance. *Third*, we also obtain expected coefficient signs for the game quality information $\{W_{gt}\}$ that becomes available as the season progresses. We find that the cumulative winning percentage of both the home and opponent teams are both positively related to attendance. The negative sign for game competitiveness indicates that fans prefer closer matchups. The negative sign occurs because the competitive variable is larger for less even matches. Interestingly, winning and losing streaks are both related to increased attendance. The "games back" (GoBack) variable indicates higher attendance when the team enjoys a higher divisional standing.

A significant aspect of our specification is that we can measure every season ticket holder's listing cost in dollar form by dividing the implied listing cost by the price coefficient, $\frac{exp(c_i)}{exp(\beta_{4i})}$. The bottom 5%, 10%, 20%, and 25% of the implied listing costs are \$2.32, \$10.78, \$56.41, and \$84.27 respectively.

The next block reports the estimation results for the intrinsic value of buying a season ticket as opposed to buying a collection of gate tickets or the no-purchase option in equation (17). The scale parameter is reparameterized as $\frac{1}{1+exp(-x)}$. The scale parameter is approximately .362. In addition, we find the intercept of single gate ticket purchases to be negative.

The bottom two blocks of Table 11 (pg.52-53) report the parameters in the demand equation for the secondary market and the demand shock variances. The estimated intercepts range from 2.243 for Tier 1 to 2.553 for Tier 6. This is consistent with the successful resale rates across seat quality tiers in Table 4. The resale rates in high quality tiers are approximately 10% lower than that in low quality tiers (e.g. 30% in Tier 1 versus 40% in Tier 6). The game quality coefficients are significantly positive. When controlling for the game quality, we find a negative relationship between list price ratio and resale probability. We also find a negative relationship between the percentage of season tickets listed on secondary markets and the resale probability. This is not trivial. Without controlling for endogeneity through game quality and augmented demand shocks ξ_{1gt} and ξ_{2gt}, the percentage of season tickets listed on secondary and the resale probability are positively correlated. This is because if a particular game has a positive secondary market shock (i.e. more demand and higher resale rates), this would increase the average listing probability as well as list prices. Our augmentation step controls for the unobserved demand shocks and corrects for the biased price coefficients. In addition, the estimated correlation of the two augmented demand shocks ξ_{1gt} and ξ_{2gt} is .595. This provides evidence that the unobserved shock to season ticket holders' perceived game quality ξ_{1gt} and the unobserved shock to secondary market demand ξ_{2gt} are different although they may be driven by some common factors.

Table 12 reports how observed individual heterogeneity, distance, years as a customer (tenure), and income affect the estimated coefficients in Table 11. We find that fans who live far away from the stadium are more price sensitive. As the price coefficient is reparameterized as $-exp(x)$, a positive coefficient of distance indicates more sensitivity. We find a lower listing cost for those who live far away. Sweeting's notion that greater distance should lead to higher resale rates is intuitive. However, in our data we tend to find a contrary result.

Our speculation is that this result is due to idiosyncratic features of the team's history and market position. The team under study has a unique history in several respects. They were essentially the only team located in a large geographic region and the team was prominently featured in the early days of cable television. This may have created a situation where the team's fan base is more geographically dispersed than other teams. Our speculation is that distance to the stadium operates differentially based on whether or not fans are located in the team's metropolitan area. Within the metro area, we suspect that distance operates as expected with greater distances being associated with higher costs of attendance. However, for fans outside of the metro area, distance may be positively correlated with preferences. Note that the identification of individual level listing cost is based on the variation in season ticket holder's relative propensities to list tickets to resell. Our identification strategy for listing costs ensures that we control for game attendance utility across individuals. We can separate out whether the low listing frequency is due to high listing costs, higher game attendance utility, or lower price sensitivity. We also find that fans with more tenure are less price sensitive compared to newer fans, and that the matched zip code level median income does not seem to affect most of the estimates.

7. Policy Analysis

Our ultimate goal is to understand whether secondary markets add value to season ticket holders and how this value influences retention rates across segments of customers. In this section we report the results from three simulation studies that use the preceding models to study how the secondary market influences season ticket purchases and revenues. The specific policy experiments are motivated by the legal and marketing landscapes related to secondary markets.

The first scenario eliminates the secondary market. The second scenario sets either a minimum or maximum price for listed tickets on the secondary market. The third scenario sets the implied listing cost to 50% of current levels.

In the simulations, we set team performance, game characteristics, and season and gate ticket prices to the levels observed in the data. The first step in the procedure is the simulation of each customer's ticket usage decisions of attending, listing, or forgoing. We obtain predicted list price ratios by applying the fixed-point algorithm such that ticket supply and demand on secondary market is at equilibrium. After obtaining the predicted list price ratio, we simulate the utility of purchasing a season ticket based on the expected usage value of the 81 game package. We also simulate the utility of not purchasing a season ticket and instead waiting to buy single game tickets. These utilities are used to predict the probability of season ticket purchase. The simulation procedure details are outlined in online appendix E.

Table 13 reports the results of the three policy experiments. We find that the absence of the secondary market decreases season ticket purchase rates by 5.97%. The tier level results are presented in Figure 3. We see the smallest impact for the highest quality tier and a steadily increasing effect on lower quality tiers. The policy results echo the data pattern in Table 4 that low quality tier ticket holders are more likely to list for resale. We further calculate the purchase rate increases impact on revenue dollars. The 5.97% increase in season ticket purchase rates provides a $3,397,294 revenue increase over 6-years.

We also consider the potential cannibalization of single game ticket sales due to the alternative supply of single game tickets on secondary markets. If the secondary market provides a reliable source of tickets, the team may end up competing with the secondary market in terms of single game sales. If this occurs, then reselling activity by season ticket holders might cannibalize the single game sales of the team.

While our modeling framework does not provide an explicit analysis of this type of cannibalization, we can compute a conservative estimate of the impact of the secondary market on single game sales. To perform this analysis, we assume that all season ticket holders' resale transactions replace purchases from the team. This is a conservative assumption, as it neglects the market expansion effects of the secondary market. Under this assumption, the successful resale activity from season ticket holders reduces single game revenues by $763,900 over the 6-year window. Taking into consideration the revenue gains from the purchase of season ticket packages and the potential cannibalization of single game gate ticket sales, the net revenue impact of the secondary market would be $2,633,394 over six years.

The second set of simulations investigates minimum and maximum listing price policies. For example, the Yankees resisted partnering with StubHub until they were able to require a minimum price for resale tickets on StubHub. For the simulation, we set the minimum list price at half of the single gate ticket price and the maximum list price to the level of the single game ticket face value. We find that the minimum list price policy reduces season ticket purchase rates by 2.28%. This is equivalent to a $1,042,918 revenue loss from season ticket holders. Not surprisingly, the impact is the largest on low quality tier season tickets. This is also consistent with the data in Figure 2 that shows that lower quality tier tickets are listed at lower price ratios on the secondary market. We find a minimal impact of capping secondary prices at the ticket face value. This may be due to the market position of the team under study. This maximum list price policy might have greater impact on teams whose selling prices deviate more from face values in the secondary market.

The third simulation sets the implied listing cost to 50%. This scenario represents a situation where consumers are more comfortable with ticket listing and the reselling procedure is less costly. The 50% listing cost scenario is predicted to increase sales by 2.70%. Eliminating list costs would bring the team an extra $1,088,576 revenue from season ticket sales. Figure 3 shows that this volume tends to be concentrated in the lower quality tiers.

8. Discussion

Our research focuses on how a legal and well developed secondary market affect sports fan's preferences for purchasing season tickets. Specifically, our data allows for a detailed analysis of how secondary market options and consumer's product usage decisions are related to customer retention. In our case, consumers have the option to directly use a ticket, resell a ticket, forgo a ticket, or purchase unbundled single game tickets. These post-purchase options and decisions highlight an important aspect of our research. Academic researchers often focus on data created by transaction processing systems but, in general, decisions related to product usage are not observable to researchers. In the case of tickets, it is increasingly possible to observe significant details related to consumption. While there is some research (Desai and Purohit 1998; Ishihara and Ching 2017; Shiller 2013) related to reselling activities, most reselling covered in the literature is related to post-initial usage behaviors.

We find that the options created by the secondary market increase the value of purchasing ticket packages. Our results suggest that the net impact of the secondary market is to increase purchasing rates by approximately 6%. This translates to increase in revenue of about $2.6 million for the team under study. Given that sports organizations have similar structures as industries with high fixed costs and perishable inventory (Cross 1997) this revenue increase has significant implications for profit rates.

Our policy experiments have important implications for teams, leagues and legislatures. We find that policies that create constraints such as minimum price floors have an adverse impact on season ticket sales. This is a complex issue since price floors may be motivated by a desire to protect brand equity. Leagues and regulators must balance these brand maintenance goals against the benefits of providing more value to teams' most valuable customers.

Our results also have implications for segment level customer management. While we focus on the overall impact of the secondary market we do observe differences based on quality of tickets purchased. One interesting aspect is that the secondary market is least impactful for buyers of the highest quality seat tier. Given the lower renewal rates for buyers of the two lowest quality seat tiers, these results suggest that increasing options and value may be a particularly useful strategy for more marginal customers. These types of results could be used to refine pricing policies or to devise segment level promotions.

As with any empirical research our findings should be interpreted based on limitations inherent to our data. For example, while we are able to observe significant post-purchase activities we do not have complete transparency. For example, season ticket holders may also distribute tickets through more informal markets such as selling directly to friends or giving away tickets to family members. These types of informal transfers provide an additional option value to consumers. These options existed prior to the creation of the secondary market. It is an open research question as to how the decision to use these type of informal markets or gift tickets is influence by the secondary market.

Furthermore, while the sample includes multiple years of data for a large number of consumers, the data is sourced from a single team. Teams vary in terms of local support and on-field performance. While the direction of the findings related to the "option value" provided by the secondary market are likely robust, the magnitude of effects may change based on underlying demand levels in different markets. For example, if a team enjoys frequent sellouts then the value provided by the secondary market may be even greater if fans can frequently sell tickets above face value. The issue of demand constraints also highlights a possible modeling extension. For teams with significant capacity constraints, expectations of ticket availability may become more salient.

A further limitation of our research is that we focus entirely on the season ticket holder segment. We choose this focus based on the managerial importance of the segment and due to data limitations. As noted (Lombardo 2012), season ticket holders often account for the majority of box office revenues. In addition, season ticket holders tend to be high CLV customers. From a data standpoint, we do not have access to detailed customer level data related to single game ticket sales. However, we do acknowledge that teams may benefit from viewing the menu of season ticket packages and single game tickets simultaneously. We leave questions such as the relative pricing of single game versus season tickets to future researchers.

One limitation of our study that suggests an avenue for future research is the single-category nature of our study. While we study the sports category, secondary ticket markets also do significant business in performing arts categories. Our basic modeling structure is largely applicable to non-sports contexts in that packages are purchased based on expected value and expected resale possibilities. However, there are likely some salient different in performing arts categories relative to sports. For example, while in sports contexts events may be differentiated based on opponents, the product might be viewed as largely similar. In contrast, a theater organization might offer very different types of plays and different collections of actors across a season. It might also be more difficult for consumers to form expectations about performance quality since there is a lack of objective data such as winning rates and payrolls.

There are other significant opportunities for future research. For example, the secondary market can also provide valuable information signals to teams. Specifically, the dynamic nature of these secondary markets can provide better information about willingness to pay for different types of tickets. There may also be opportunities to investigate the role of consumer learning. Finally, there are certain contexts related to season tickets that would call for a dynamic programming model. If a club had a significant waiting list or a quality based seniority system, the consumer's renewal decision would need to consider the long-term benefits of buying tickets in terms of being to acquire higher quality tickets and that cancellation might make it difficult to buy tickets in subsequent years.

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Tables

Table 1: Season Ticket Tier Choices % by Season

	Season 2011	Season 2012	Season 2013	Season 2014	Season 2015	Season 2016
Tier 1	12.47	11.54	10.97	11.64	11.07	7.95
Tier 2	21.21	20.06	20.01	19.59	18.40	14.66
Tier 3	13.05	11.49	11.02	11.07	10.45	8.75
Tier 4	11.22	10.55	11.28	11.80	11.17	8.94
Tier 5	9.15	9.56	9.36	9.62	7.54	5.72
Tier 6	6.60	7.28	7.07	6.44	5.41	4.26
No Purchase	26.30	29.52	30.30	29.83	35.97	49.74

Table 2: Season Ticket Renewal Rate% by Tier

(t-1) (t)	No Purchase	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Tier 6
No Purchase	79.40	14.23	11.10	15.48	15.58	22.30	23.93
Tier 1	2.39	84.23	0.73	0.18	0.19	0.00	0.00
Tier 2	3.28	0.90	87.43	0.46	0.19	0.00	0.16
Tier 3	2.74	0.36	0.31	83.42	0.37	0.57	0.00
Tier 4	4.11	0.27	0.31	0.27	82.93	0.80	0.16
Tier 5	4.58	0.00	0.00	0.09	0.65	75.86	0.32
Tier 6	3.49	0.00	0.10	0.09	0.09	0.46	75.44

Table 3: Season and Single Ticket Price ($) per Game by Tier

	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Tier 6
Season Ticket Price per Game ($)	54.30	46.14	31.80	22.33	12.47	8.19
	(1.97)	(1.25)	(1.32)	(3.12)	(0.60)	(0.43)
Single Ticket Price per Game ($)	85.18	75.92	52.24	41.31	29.86	17.92
	(13.78)	(13.00)	(11.45)	(9.94)	(8.25)	(5.48)
Percentage of Sales						
% of Season Tickets	86.7	83.5	66.0	60.2	30.8	25.1
% of Non-Season Tickets	13.3	16.5	34.0	39.8	69.2	74.9

Note: (1) standard deviations in parentheses; (2) variations of season ticket prices come from across seasons, while variations in single ticket price come from both across seasons and across games within a season.

Table 4: Season Ticket Intended and Actual Usage Patterns by Tier (in %)

	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Tier 6
Intended Usage						
Attendance	71.21	70.31	68.34	66.02	57.54	50.42
Forgo	21.80	23.86	25.03	29.78	34.53	37.59
Listing	7.00	5.82	6.62	4.19	7.92	11.99
Actual Usage						
Attendance	74.55	73.05	71.64	67.42	59.59	52.75
Forgo	23.34	25.14	26.37	30.94	37.16	42.32
Resold	2.10	1.82	2.00	1.64	3.25	4.93
Conditional Usage						
Successful Resale Rates	30.07	31.26	30.14	39.04	41.06	41.12
Not Sold but Choose to Attend	47.83	46.98	49.70	33.33	25.86	19.39
Not Sold but Choose to Forgo	22.10	21.77	20.17	27.62	33.08	39.49

Table 5: Ticket List and Resale Transaction Price ($) per Game by Tier

	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Tier 6
List Price per Game	83.08	72.79	49.51	38.37	27.09	15.16
	(21.86)	(22.28)	(17.32)	(15.32)	(12.30)	(8.32)
Resale Price per Game	54.65	51.47	34.31	27.15	18.42	9.93
	(18.43)	(18.64)	(13.92)	(12.80)	(9.90)	(6.30)
Season-to-Single Price Ratio	0.65	0.63	0.64	0.57	0.46	0.51
	(0.11)	(0.11)	(0.14)	(0.16)	(0.14)	(0.19)
List-to-Single Price Ratio	0.97	0.95	0.94	0.92	0.89	0.84
	(0.17)	(0.19)	(0.20)	(0.23)	(0.25)	(0.31)
Resale -to-Single Price Ratio	0.64	0.67	0.65	0.64	0.60	0.55
	(0.16)	(0.17)	(0.18)	(0.24)	(0.25)	(0.32)

Note: standard deviations in parentheses; the variation in list and resale prices comes from cross seasons, cross games within a season, as well as cross-individuals.

Table 6: Secondary Market Prices and Sales

	Logistic Regression on Resale			Linear Regression on Listing Price Ratio			Linear Regression on Resale Price Ratio		
	Estimate	S.E.		Estimate	S.E.		Estimate	S.E.	
Game Quality Index	0.720	0.012	***	0.067	0.008	***	0.127	0.008	***
% of Listing (log)	-0.182	0.025	***	-0.023	0.005	***	-0.073	0.008	***
List price ratio	-3.238	0.033	***						
Seat Tier Dummies		Included			Included			Included	
Game Random Effect					Included			Included	
# of Observations	41,681			41,681			14,496		
R-Squared				0.071			0.072		

Note: (1) ***, **, * indicates p-value <0.01, <0.05, and <0.1; (2) we use the whole sample of season ticket holders listing on secondary market to model the resale outcome and listing price ratio, and use the subsample of successfully resold ticket to model the market equilibrium resale price ratio; (3) we also include game level random effects for the listing price ratio and resale price ratio regressions.

Table 7: Game Level Listing Decision and the Possibilities of Forward Looking

	Estimate	S.E.	T value	p-value	
Current Period Game Quality Index	0.049	0.012	3.909	<0.001	***
Future Period Game Quality Index (g+1)	0.019	0.015	1.286	0.199	
Future Period Game Quality Index (g+2)	-0.012	0.015	-0.787	0.431	
Future Period Game Quality Index (g+3)	0.013	0.015	0.878	0.379	
Future Period Game Quality Index (g+4)	-0.011	0.015	-0.695	0.487	
Future Period Game Quality Index (g+5)	-0.007	0.013	-0.527	0.598	
Individual Average Listing Rate	6.179	0.033	190.765	<0.001	***
Individual Average Forgone Rate	0.173	0.053	3.236	<0.001	***
Seat Tier Dummies	Included				
# of Observations	188,976				

Note: (1) ***, **, * indicates p-value <0.01, <0.05, and <0.1; (2) Game-level listing decision (Yes=1/No=0) is the dependent variable; (3) we control for cross-individual variation with individual average listing rate and forgo rate in each season; (4) we use the logarithm of total revenue from gate ticket sales as an approximation for game quality index.

Table 8: Average Number of Games Purchased When Not Purchasing Season Tickets

	Average # Games Purchased via Primary Market	Average # Games Purchased via Online Secondary Market
In the year not renewing a season ticket	14.20	0.12
In the year prior to a season ticket purchase	23.48	0.23

Table 9: Panel Logistic Regression of Season Ticket Renewal and Secondary Markets

	Estimate	S.E.	T value	p-value	
AttdRate	0.688	0.015	45.542	<0.01	***
ListRate	0.152	0.032	4.717	<0.01	***
ResaleRate	-0.075	0.032	4.717	<0.01	***
ResalePriceRatio	-0.022	0.025	-0.885	0.376	
ResaleRate×ResalePriceRatio	0.141	0.078	1.800	0.072	*
s.d. β_{oi}	0.156	0.006	24.913	<0.01	***
s.d. ϵ_{it}	0.343	0.003	121.763	<0.01	***
Season Dummies	Included				

Note: ***, **, * indicates p-value <0.01, <0.05, and <0.1.

Table 10: Season Ticket Purchase Hit Rate by Tier

	Hit Rate
Overall	89.46
Tier 1	87.30
Tier 2	91.10
Tier 3	89.60
Tier 4	87.50
Tier 5	80.80
Tier 6	82.30
No Purchase	93.30

Table 11: Estimation Results

	Estimate	2.5 Percentile	97.5 Percentile
Game attendance variables X_{gt} available at season ticket purchase stage			
Tier 1	-3.543	-3.821	-3.284
Tier 2	-2.759	-3.015	-2.535
Tier 3	-3.639	-3.903	-3.418
Tier 4	-4.169	-4.419	-3.947
Tier 5	-4.525	-4.830	-4.324
Tier 6	-5.420	-5.662	-5.232
Season 2012	-0.021	-0.100	0.101
Season 2013	0.052	-0.015	0.120
Season 2014	-0.077	-0.144	0.005
Season 2015	-0.312	-0.366	-0.253
Season 2016	-1.031	-1.126	-0.895
Weekend	0.563	0.506	0.675
Night	0.519	0.467	0.546
Holiday	0.020	-0.033	0.079
OppWin% (t-1)	1.446	0.950	1.973
OppRelPay (t)	0.455	0.390	0.508
Game attendance variables W_{gt} available at ticket usage stage			
HomeCumWinPt(gt)	0.953	0.798	1.063
OppCumWinPt(gt)	0.648	0.167	1.247
Competitiveness (gt)	-0.638	-0.798	-0.250
StreatkWin (gt)	0.035	0.017	0.052
StreakLoss (gt)	0.052	0.045	0.060
GoBack (gt)	-0.188	-0.279	-0.159
Game listing variables			
Listing Cost	1.598	1.485	1.635
Price coefficient of Season Ticket Holders	0.371	0.347	0.396
Ticket purchase intercept and scale			
Season Ticket Intercept	-4.002	-4.089	-3.892
Single Ticket Intercept	-1.407	-1.715	-1.209
Scale τ_i	-1.141	-1.258	-0.957
Secondary Market Parameters			
Gamma tier1	2.243	2.163	2.336
Gamma tier2	1.868	1.663	2.104
Gamma tier3	2.510	2.384	2.631
Gamma tier4	2.565	2.419	2.682
Gamma tier5	2.666	2.593	2.727
Gamma tier6	2.553	2.470	2.715
Quality coefficient A_{jgt}	0.530	0.410	0.679
% of season tickets listed L_{jgt}	-0.172	-0.202	-0.105
Price coefficient of secondary market	1.071	1.067	1.085

Variance of ξ_{1gt}	.216	.189	.243
Variance of ξ_{2gt}	1.323	1.169	1.522
Cor between the two shocks ξ_{1gt} and ξ_{2gt}	0.595	0.526	0.660
Log-likelihood	-745,265		

Note: price coefficients are reparameterized as -exp(.), cost coefficients are reparametrized as exp(.), and scale coefficient is reparameterized as $\frac{1}{1+\exp(-x)}$.

Table 12: Observed Individual Heterogeneity

	Demeaned Distance	Demeaned Tenure	Demeaned Income
Tier 1	-0.220	**2.410**	0.376
Tier 2	-0.130	**2.621**	0.342
Tier 3	**0.434**	**2.604**	0.110
Tier 4	0.027	**2.265**	-0.121
Tier 5	**0.434**	**1.557**	-0.757
Tier 6	0.085	**2.332**	-0.165
Season 2012	**0.097**	**-0.707**	-0.106
Season 2013	-0.002	**-1.511**	0.042
Season 2014	**-0.134**	**-1.670**	0.083
Season 2015	-0.118	**-1.812**	0.117
Season 2016	**-0.172**	**-1.636**	0.020
Weekend	**0.091**	**-0.079**	-0.153
Night	-0.025	0.027	0.043
Holiday	**0.034**	0.014	-0.069
OppWin% (t-1)	-0.036	-0.298	-0.370
OppRelPay (t)	0.006	**-0.042**	0.006
HomeCumWinPt(gt)	-0.006	-0.019	-0.117
OppCumWinPt(gt)	-0.092	-0.177	-0.590
Competitiveness (gt)	0.023	**-0.314**	-0.271
StreatkWin (gt)	0.003	0.005	-0.006
StreakLoss (gt)	0.004	-0.005	-0.005
GoBack (gt)	0.006	-0.013	-0.012
Listing Cost	**-0.393**	**0.234**	-0.369
Price coef of Season Ticket Holders	**0.167**	**-0.234**	0.054
Season Intercept	0.060	**0.286**	**0.524**
SingleIntercept	-0.037	**1.306**	0.054
Scale τ_i	**-0.431**	**1.339**	-0.487

Note: bold refers to 95% highest density interval does not cover zero

Table 13: Policy Experiments

	Season Ticket Purchase Rate Difference	Revenue Change ($)
No secondary market	-5.97%	-3,397,294
Minimum list price policy	-2.28%	-1,042,918
Maximum list price policy	0.14%	54,744
Listing cost reduced to 50%	2.70%	1,088,576

Note: the difference refers to purchase rate differences in the counterfactual setting and the baseline prediction setting.

Figures:

Figure 1: Intended Usage Patterns by Seasons

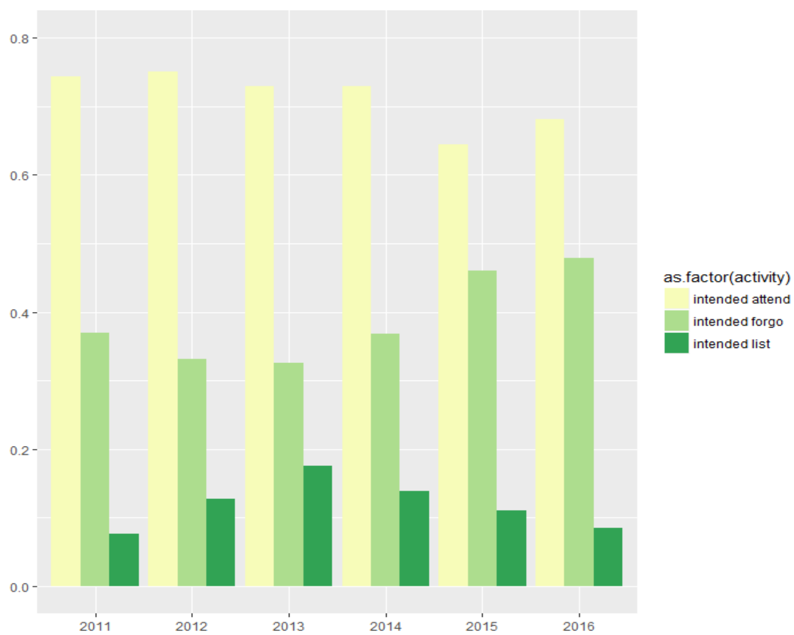
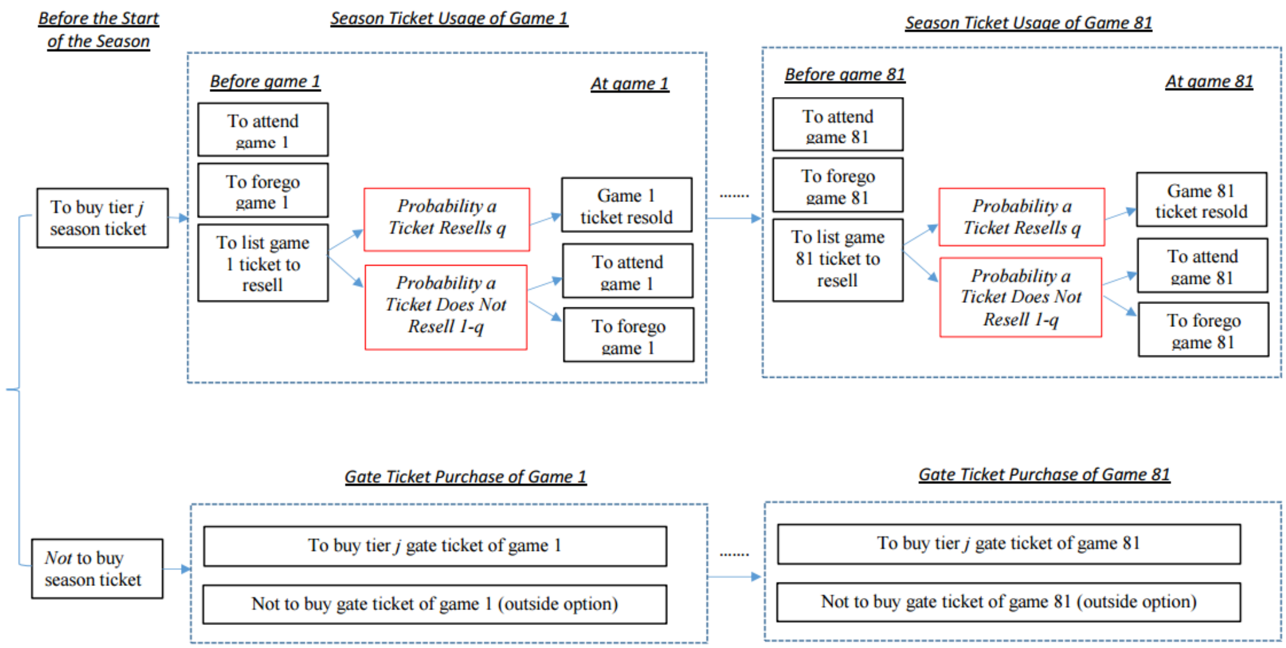


Figure 2[3]: Illustration of Decision Process



[3] We do not model the option of season ticket holders purchasing single tickets from secondary markets, because even when choosing not to buy season packages, individuals buy from the team website. Less than 1% of the time did they choose to buy single tickets from secondary markets rather than the team directly. We acknowledge that this could be due to the team under study. Yet our model can be extended to accommodate single ticket purchase option from secondary markets for other teams.

Figure 3: Policy Experiment Results by Tier