Scoring a Touchdown with Variable Pricing: Evidence from a Quasi-Experiment in the NFL Ticket Markets

Business of Sports
1548725

Abstract

Event organizers are moving from fixed to variable pricing. Although this is theoretically shown to enable organizers to respond to changing demand across events, reports point to somewhat limited implementation due to the unpredictable nature of the popularity of an event and to the unaccounted-for dynamics of the resale market. In this paper, we study the implications of a switch to variable pricing using a quasi-experimental data from the National Football League. Applying a difference-in-differences technique with propensity-score weighting, we find that teams switched to variable pricing sold 2.95% additional tickets per game through the primary market. We provide suggestive evidence that this positive effect is due to the quality-signaling nature of variable pricing for price-sensitive customers. Specifically, we find that variable pricing resulted in higher primary market sales at (i) games in hometowns with lower income levels and higher income diversity, and (ii) unattractive games. We also explore whether variable pricing led to any negative effects through the resale market. With variable pricing, although the number of ticket listings in the resale market went up for unattractive games, customers did not list their tickets at lower prices. This indicates that variable pricing did not lead to cannibalization from resale markets. For attractive games, the minimum listing price in the resale market increased. This shows that the display of popularity through teams' higher prices increased the option-value for these games, and explains why the primary market ticket sales remained steady for attractive games, even after the increase in prices.

Key words: ticket pricing, resale markets, sports events, quasi-experiment, difference-in-differences, propensity-score weighting

1. Introduction

Event organizers, such as sports games or music shows organizers, enable their customers to purchase tickets prior to the beginning of the season. The content of events within a season often varies, and customers may value each event differently. In these settings, a fixed price strategy may not be sufficient to maintain high attendance and maximize revenue in all the events across the season, since it favors meeting the demand for the most popular events and leaves the others underutilized (Phillips 2005). As a result, organizers increasingly favor variable pricing tactics where they pre-set varying prices across events (Kline 2019, Stevenson 2019). Variable pricing enables organizers to respond to changing demand across events and allows the customers to self-select into their preferred alternative. However, reports point to somewhat limited implementations and suggest some reservations on the part of organizations (Engber 2017). This is not surprising considering revenue management for events is a complex problem that involves price decisions that are prone to uncertainty. In particular, the unpredictable nature of the popularity of a sports event or a new show (Xu et al. 2019), and the potential cannibalization of primary market sales by secondary markets (Talluri and van Ryzin 2004) may cause organizations to hesitate. Although this has led to a growing interest in studying the primary and secondary market dynamics under different pricing strategies (Su 2010, Cui et al. 2014), the academic literature lacks empirical studies investigating the implications of variable pricing in a quasi-experimental setting. Hence, we begin by asking a fundamental question: How are event organizers' primary market sales affected when they switch from fixed to variable pricing for their events?

An answer to this question requires an examination of customers' actions in secondary markets in addition to their actions in the primary market, since event tickets are often transferable. Customers' perception of the likelihood of demand to exceed ticket availability can be a major determinant of their purchase decisions. If they anticipate that the event will sell out, they may believe that their tickets can be easily resold in the secondary market. This option to resell, which is defined as the *option-value effect*, can encourage customers to purchase tickets from the primary market (Bennett et al. 2015). If sell-out is unlikely, on the other hand, customers can be reasonably sure to find tickets available in the secondary market at lower prices. In that case, the *cannibalization effect* will take over, leading customers to defer their ticket purchases to the secondary market (Bennett et al. 2015). Note that customers' purchase decision depends on their perception of the popularity of an event. Consistent with the literature (Preuss 2007), we term this perception as *attractiveness* of an event. We argue that a variable pricing strategy can disclose information about the organizer's belief in which events are attractive to customers and influence customer purchasing decisions. A low-priced event will signal that an event is less attractive and can prevent the deferral of purchases to the secondary market. Although this suggests that some cannibalization can be prevented, the increasing number of customers who have purchased tickets from the primary market has the potential to become a threat later in the season by posting their tickets in the secondary market. Hence, the net effect of variable pricing for low-priced events is unclear. Although the reasons are different, the net effect for high-priced events is also unclear. A high-priced event will signal that an event is more attractive and can activate the option-value effect. However, this demand-boosting effect can be negated by the price increase due to variable pricing. Validation of these dynamics requires a comprehensive look at the activity in the primary and secondary markets. We aim to validate the secondary market dynamics behind the changes in the primary market by also answering the following question: How does a switch from fixed to variable pricing affect the number of ticket listings and the ticket prices posted in the secondary market?

To answer these questions, we assemble a novel dataset that includes game-level primary market ticket sales, number of ticket listings in the resale market, and minimum ticket listing prices in the resale market before and after the period when the NFL first allowed teams to use variable pricing tactics (just before the 2014 season). At that time, 15 out of 32 NFL teams switched from fixed to variable pricing. The main challenge in measuring the effects of this switch is that it is a strategic decision by teams, thus potentially not random. Hence, a simple comparison of the primary and resale market activities between games of teams which switched to variable pricing and games of those which did not switch may be misleading, especially if there are differences across teams or games (e.g., demographic differences across home game locations).

To address this endogenous switch-selection threat for the identification, we employ a propensity-score weighted difference-in-differences method at the team-game level. This quasi-experimental approach ensures that treated and non-treated games are comparable in terms of pre-treatment trends of primary and resale market activities, and several important variables that might influence a team's decision to switch to variable pricing.

We find that the teams which implemented variable pricing tactics sold 2.95% additional tickets on average per game. As expected, this increase is negatively moderated by 0.64% for each percentage increase in the average ticket prices after switching to variable pricing. To verify that the positive average effect is mainly due to the quality-signaling role of variable pricing, we also explore the likely mechanisms. We present two types of suggestive evidence that supports the quality-signaling role. First, we find that the switch to variable pricing has a more positive sales effect in towns with lower income levels and higher income diversity. Second, while the switch to variable pricing resulted in higher sales for less attractive games, we did not find a significant change in the sales for more attractive games. These findings confirm that variable pricing got the attention of price-sensitive customers, who with fixed pricing, were more likely to defer their purchases to the resale market to avoid paying higher prices for games with unpredictable attractiveness.

To show that these additional primary market ticket sales did not lead to unexpected competition from the resale market, we also perform an analysis on differences in customers' activities in the resale market after the switch to variable pricing. First, we find that, on the average, the number of ticket listings in the resale market increased for less attractive games and decreased for more attractive games after the switch to variable pricing. Hence, variable pricing could create a competition threat from the resale market for less attractive games. Second, we find that customers did not decrease their ticket listing prices in the resale market for the less attractive games. In the end, customers' decision to not set lower prices means that the additional listings in the resale market are not a threat for the teams that switched to variable pricing. As per the more attractive games, we find that the minimum ticket listing prices in the resale market went up on average after the switch to variable pricing. This confirms that the display of popularity through the teams' higher prices activated the option-value effect, and explains why the primary market ticket sales remained steady, even after the increase in prices.

The remainder of the paper is organized as follows: In §2, we provide a detailed review of the related literature and position our work. In §3, we discuss our quasi-experimental context. §4 presents our data and some model-free evidence for our conjectures. In §5, we present our findings from the analysis of changes in primary market ticket sales. §6 provides the mechanism behind our results. In §7, we supplement our primary market findings by exploring changes in resale market activity. In §8, we provide insights into our results and conclude.

2. Literature Review

This paper is primarily related to three streams of literature: price discrimination and variable pricing, secondary markets, and the value of disclosing information for organizations. We review each stream and highlight our contributions below.

Price discrimination across different seating categories is common in the entertainment industry. As the theory of second-degree price discrimination predicts (Pigou 1932), seat-based price discrimination can sort customers with different preferences towards various seating areas and help organizations maximize the surplus extracted from distinct customer groups. Rosen and Rosenfield (1997) show that the return from seat-based price discrimination depends on the relative variance of customer willingness-to-pay for each seat category. Courty and Pagliero (2012) complement this finding by showing empirical support from the North American concert industry. By using data from a Broadway theater, Leslie (2004) further shows that a switch to seat-based price discrimination from uniform pricing can lead to revenue improvements without significant changes in aggregate consumer welfare. We add to this stream of research by considering qualitative differences not just across different seating categories, but also across an organization's multiple events in a season.

Some event organizations recently switched to variable pricing strategies for their multiple events across a season. Since their venues have a fixed number of seats and the interest toward their events varies across a season, uniform or fixed pricing strategies often result in an excessive number of leftover tickets or an early sell-out. To tackle such a mismatch of demand and capacity, variable pricing strategies have been implemented in a variety of field settings: peak-load pricing by utility providers (e.g., Vickrey 1971, Kök et al. 2018), surge pricing on service platforms (Cohen et al. 2016, Cachon et al. 2017), congestion pricing for parking spaces (Feldman et al. 2018), or price discrimination with advance-selling for entertainment products (e.g., Gale and Holmes 1993, Gallego and Şahin 2010, Cachon and Feldman 2017). Yet, the implementation of variable pricing is limited in the entertainment industry and its implications have been understudied. To our knowledge, the only paper discussing an application of variable pricing is Arslan et al. (2019), which develops a pricing tool for a college football team. We contribute to this line of research by empirically measuring the impact of variable pricing in the NFL through a quasi-experimental setting. We offer insights on (i) the mechanisms through which variable pricing affects the primary market ticket sales, and (ii) whether variable pricing led to negative effects through the resale market.

There is recent interest in dynamic pricing of events for entertainment organizations. Similar to other dynamic pricing settings with nonhomogeneous demand (as first considered by Zhao and Zheng 2000), the popularity of a particular event could also change based on some exogenous factors such as team performance. Unlike other dynamic pricing settings, our setting involves both horizontal (e.g., different games) and vertical (seating categories) differentiation. For settings with both horizontal and vertical differentiation, Akçay et al. (2010) and Transchel (2017) provide insights on the theoretical properties of the optimal pricing solution. Xu et al. (2019) introduce a regression-based forecasting model that captures nonhomogeneity of demand and show empirically how revenues can be improved for a Major League Baseball franchise. Our research goal is to fill the gap in empirical evidence on the returns from variable pricing. For this reason, we focus on a context where dynamic pricing had not yet been implemented.

Our work is also related to the research on secondary markets. Since event tickets are often transferable, we need to consider how customers react to different pricing strategies in the existence of a secondary market. The well-established finding in the secondary market literature is that used-good markets cannibalize new product sales (Suslow 1986). Yet, active secondary markets can also benefit producers through indirect price discrimination opportunities (Anderson and Ginsburgh 1994, Hendel and Lizzeri 1999, Chen et al. 2013). In the context of ticket pricing, Bennett et al. (2015) show that resale markets can have two effects on customers' purchase decisions. When the seats are likely to sell out, customers can be reasonably certain that they can resell their tickets in the resale market. This option to resell provides additional value and can encourage customers to purchase tickets from the primary market, which is defined as *the option-value* effect. When sell-out is unlikely, customers can easily anticipate that tickets will be available in the resale market at lower prices. In that case, *the cannibalization effect* will take hold, resulting in customers deferring their ticket purchases to the resale market. In fact, a recent survey conducted by Connolly and Krueger (2018) shows that resale accounts for 10% of all tickets purchased in the concert industry. Trefis Team (2017) reports that Stubhub revenues and gross merchandise volume increased by 30% in 2016. The significant size of the resale market and increasing availability of resale market data (Rishe 2014) also explains the recent academic interest on understanding customers' decisions in primary versus resale market purchases.

This research stream explores the implications of the existence of a resale market by modeling different types of customers' purchase decisions. One side of this research stream focuses on showing how the presence of scalpers, who purchase tickets for popular events in advance from the primary market for the purpose of reselling at a higher price later in the resale market, influence the event organizers' revenues. Su (2010) shows that organizations can increase their expected profits by selling tickets early and transferring the inventory risk to scalpers. Cui et al. (2014) identify scenarios in which the presence of scalpers may have positive effects and suggest selling ticket options to increase revenues. Unlike these papers, Sweeting (2012) focuses on modeling the pricing decisions of resellers in the resale market and shows that simple dynamic pricing models perform well in explaining their dramatic price cuts. Another side of this research stream aims to empirically show the effects of having a resale market on organizations' outcomes. Leslie and Sorensen (2014) show that the existence of a resale market can increase the allocative efficiency of seats by 5% by utilizing data from the rock concert industry. Lewis et al. (2019) show that the existence of a resale market increases season-ticket purchases for a Major League Baseball team. Zou and Jiang (2018) further show that both content producers, organizers, and consumers can benefit from the existence of a resale market if primary ticket platforms control the resale market. All of these findings show that a thorough comprehension of the effects of a new pricing policy requires a clear observation of resale market activity, as well as primary market activity. Hence, in this paper, we do not just empirically show the final net effect of switching to a variable pricing strategy on organizations' primary market sales, but also explore customers' ticket listing behavior in the resale market.

Research on the value of disclosing information for organizations is also relevant to our study. Recently, operations management researchers explored the implications of disclosing product availability information, such as service levels (Gaur and Park 2007), sharing availability through cheap talk (Allon and Bassamboo 2011), aggregate inventory levels (Cui and Shin 2018), reliable inventory levels in online-offline integration (Gallino and Moreno 2014), seat availability for orchestra shows (Tereyagoglu et al. 2018), and remaining inventory levels for items sold through promotions (Cui et al. 2019). During a season of events, it is often difficult for consumers to anticipate which events will be popular especially when they make a purchasing decision on season-tickets. It is well-established that price levels signal product quality (e.g., Bagwell and Riordan 1991). For this reason, an organization setting lower or higher prices for events under a variable pricing policy would also signal the anticipated popularity for these events. Our paper adds to this literature by exploring how consumers react to the disclosure of popularity through the variable pricing strategy of an event organizer.

3. Background Information and Empirical Context

In this section, we provide details about the National Football League pricing strategy shift which we used to evaluate the effect of variable pricing on primary market sales.

3.1. The National Football League

The National Football League (NFL) is a professional American football league consisting of 32 teams competing in two conferences, the National Football Conference (NFC) and the American Football Conference (AFC). Each conference is further divided into four divisions of four teams each. Each team plays 16 games (8 home and 8 away) in the regular season which runs from early September to late December. A team's schedule is set using a formula: Six games against three division rivals (one home and one away game against each rival), eight games against all the opponents from one division from the NFC and one division from AFC on a rotating basis (one game for each), and two games within the conference based on previous season performance. At

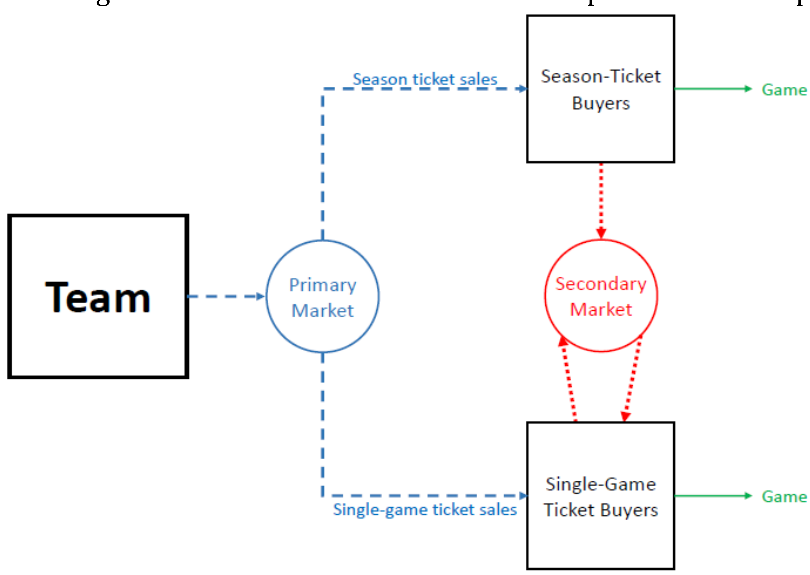

Figure 1. Customers' Interactions in NFL Primary and Resale Ticket Markets

the end of a season, six teams from each conference advance to the playoffs. In this study, we focus on the regular season games, since the pricing decisions for playoff games are conditional on a team's appearance and made right before the playoff games (as opposed to at the beginning of the season like regular season-ticket pricing decisions).

NFL teams sell two types of tickets: (i) season-ticket packages (i.e., a bundle which grants the holder access to all home games for one season), and (ii) single-game tickets. These tickets can be accessed through primary markets such as team website, box office, or authorized sellers such as Ticketmaster.

Customers that bought tickets from primary markets can sell their tickets through online resale ticket marketplaces such as Stubhub. This may occur if a customer is not able to attend a game or if the game has become so popular that the customer can make additional money by selling a ticket above its face value. Figure 1 provides an overview of customers' interactions in primary and resale markets.

The availability of tickets in both primary and resale markets creates interesting dynamics for customers' purchase decisions. If a customer purchases a season-ticket, a seat for every game is guaranteed, but the customer risks overpaying for potentially unattractive games that she does not wish to attend. A customer can avoid such unattractive games by purchasing single-game tickets. However, if the game turns out to be popular, a seat may not be available. The existence of a resale market creates flexibility for both customer types against potential negative outcomes: It provides the opportunity for season-ticket buyers to sell unattractive game tickets and recover their losses. It also helps single-game ticket buyers to find tickets for sold-out games. Although the existence of a resale market can offer such benefits for customers, it can also hurt the teams' primary market sales. We argue that teams can use variable pricing to influence a customer's belief about the attractiveness of games and prevent a customer shift to the resale market.

3.2. Variable Pricing in the National Football League

Across all major sports leagues in the United States, the NFL is known for holding on longest to a fixed pricing scheme. The major reason for this hold-out against switching to a variable pricing strategy is the low number of home games in each NFL season. However, just prior to the 2014 season, the NFL allowed teams to individually decide whether to continue with fixed pricing or switch to variable pricing. Major news outlets point to the superiority of variable pricing in setting the prices according to expected popularity of games, in recouping value lost to the resale market, in providing more value and transparency to the season-ticket buyers, and most importantly in increasing sales in the primary market as reasons for the eventual NFL switch (Fisher 2014). These objectives also align with the league's revenue improvement goals to increase attendance (which has a direct impact on future television and sponsorship contracts, Phillips (2017)), and to prevent potential television blackouts (Drayer et al. 2012).[1]

Due to the short preparation time until the release of the coming season's game schedule in April 2014, only 15 of the 32 NFL teams were able to implement variable pricing. For teams that switched to variable pricing, customers could see the pre-set variable prices for all games. Most importantly, there were no other systemic changes that would affect teams at that time.

In this quasi-experimental setting, we examine how the shift to variable pricing affects ticket sales in the primary market, the volume of tickets listed in the resale market, and the listed ticket prices in the resale market. Since variable prices for different games can disclose a team's belief of which games will be attractive, customers' purchase decisions can be affected in two ways. First, a low-

[1] Until the end of the 2014 season, the NFL forbade televising in a team's local market if 85% of the tickets were not sold three days prior to the start time of the game.

priced game will signal that a game is less attractive and could lead customers to switch from the resale to the primary market because of the lower prices compared to fixed pricing (i.e., weakening cannibalization effect); and second, a high-priced game will signal that a game is more attractive and make more customers to purchase from the primary market through the option-value effect.

4. Data and Model-Free Analyses

We merge data from seven sources to estimate the effect of the change from fixed to variable pricing on ticket sales: 1) the NFL website, 2) Internet Archive's Wayback Machine search tool, 3) Team Marketing Report, 4) Pro-Football-Reference.com, 5) SportsOddsHistory.com, 6) Brandeis University Heller School for Social Policy and Management's DiversityData.org project, and 7) the United States Census Bureau. We provide the details of these data sources below.

4.1. Primary Market Sales and Resale Market Listings Data

Our primary dataset contains information on the paid attendance of each game in a regular season of the NFL, which is collected and shared by NFL.com. To obtain this data, we downloaded all the NFL game books for each regular season game in 2012-2014.[2] Each game book reports the paid attendance of the corresponding game. Brown (2011) and Bachman (2018) point that it has become a norm for teams to report their actual ticket sales data as their paid attendance numbers. Hence, we use the paid attendance numbers in the NFL game books as our primary market sales data.

Our second source of the data is Internet Archive's Wayback Machine search tool[3], which enables us to collect two factors summarizing the resale market activity for each regular season game. Specifically, we searched for archived webpages of the ESPN website. During these three seasons, Stubhub was in a partnership with ESPN, and provided real-time information to ESPN on the number of tickets listed and the get-in price (i.e., the lowest ticket price in the resale market) in its resale market. However, this data is not available for every day. Therefore, we focused on August 1st and September 1st (i.e., a month, and right before the NFL regular season) for each season between 2012 and 2014, which provided us with a comparable data for each game in the season. We use the averages for these two records, the number of tickets listed and the get-in price, across the two days to examine how customers' resale market activities changed after teams switched to variable pricing.

4.2. Supplementary Sources of Data

We utilize multiple resources to obtain additional team- and demographics-related information to use as controls and/or balance consumer markets of teams in our analysis. We captured teams' seating maps and ticket prices using the snapshots of team websites accessed through the Internet Archive's Wayback Machine search tool. Data on teams' average ticket prices came from the annual reports of Team Marketing Report.[4] We used Pro-Football-Reference.com to obtain additional team-related data on stadium capacity, number of championships won, and the

[2] For an example, see https://nflcdns.nfl.com/liveupdate/gamecenter/56170/SEA_Gamebook.pdf
[3] https://archive.org/web/
[4] https://teammarketing.com

previous year performance for every season in 2012-2014. We also collected preseason and weekly Vegas odds for a team to win the Super Bowl, provided by the SportsOddsHistory.com, to take the team's expected strength and real-time performance into account, respectively.

In addition, we collected demographic data for each team's hometown. We obtained information on population and income (median household income and the Gini coefficient of income) from the United States Census Bureau's website[5], and ethnic diversity from Brandeis University Heller School for Social and Management's DiversityData.org project[6]. Our final dataset is composed of all the previously mentioned records for all 32 teams in the NFL. We also reviewed news articles on Factiva to determine if any of the teams experienced a major facilities infrastructure change or a public relations disaster during our observation period. We found that the San Francisco 49ers started to play their games in the new Levi's Stadium in the 2014 season, the Minnesota Vikings had to move to the University of Minnesota Stadium for the 2014 season after the Metrodome's roof collapsed due to a snowstorm, and the Tennessee Titans franchise was reported to have been illegally using a Florida-based broker to maintain its sellout streak since 1999. Hence, we excluded the home games of these three teams from our dataset. We also checked if any one of the remaining teams' home games were played outside their home stadium due to either NFL's earlier

Table 1. Descriptive Statistics and Raw Data Patterns

Variables	N	Mean	Std.Dev.	Max	Min
Team-game level variables					
Primary Market Sales	688	68,444.7	8,400.3	95,595	43,641
Resale market get-in price	688	60.6	42.7	234.5	5
Number of resale tickets listed	688	6,121.3	3,118.2	18,024.5	1,605
Primary market minimum price	544	40.9	15.8	81	19
Weekly Super Bowl odds (%)	688	4.7	7.5	4.4	0.0
Team-season level variables					
Average ticket price	87	81.5	17.8	122.0	54.2
Seat capacity	87	70,964.9	6,206.9	82,500	53,286
Preseason Vegas odds (%)	87	4.4	4.2	20.0	0.5
Previous season perf.	87	1.4	0.8	4	0
Gini Income (%)	87	46.8	1.9	50.6	43.2
Gini Ethnicity (%)	87	53.0	12.9	71.0	24.0
Median Income	87	58,321.4	11,046.6	91,756	43,136
Population (millions)	87	4.5	4.7	19.9	0.1

Model-free evidence for the change from fixed to variable pricing

	Teams that did not switch to variable pricing	Teams that that switched to variable pricing	Difference (p-value)
% change in ticket sales per game in the primary market after the change	0.2%	3.2%	3.0% (0.01)

promotional commitment (i.e., internationally hosted regular season games) or unexpected extreme weather (i.e., a snow storm). We found nine such games and excluded them from our

5 https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

6 http://www.diversitydata.org/ provides the ethnic heterogeneity tables for each team's home town. We use the tables to calculate the Gini coefficients for ethnic diversity.

analysis.[7]

4.3. Raw Sales Around the Change from Fixed to Variable Pricing

The upper panel of Table 1 shows the summary statistics for key variables used in our estimations. The lower panel of Table 1 shows the raw difference-in-differences in terms of percentage changes in unit ticket sales in the primary market for teams' home games that are affected by the change to variable pricing (i.e., treatment group) and those that are not (i.e., control group). The differences show that primary ticket sales increased more for treated games relative to control games. We use econometric analyses to validate this insight in Section 5.

4.4. Other Potential Shifts Around the Change to Variable Pricing

We also examine other potential changes in teams' selling strategies around the time teams shift to variable pricing that might confound the relationship between ticket sales in the primary market and a shift to variable pricing. In particular, we look for a change in teams' stadium capacity and average ticket price around the time they shift to variable pricing. We find that the difference between average seating capacities of teams across 2013 and 2014 is only 97.58, which is not statistically significant ($p > .10$). We similarly find that the difference between average ticket prices of teams across 2013 and 2014 is only 1.38, which is not statistically significant ($p > .10$). This implies that the seating capacity and average ticket prices for treated teams do not change significantly around the time these teams shift to variable pricing.[8]

5. Effect of the Shift from Fixed to Variable Pricing on Customers' Purchase Decisions

In this section, we examine the main effect of the switch from fixed to variable pricing on ticket sales in the primary market. The key empirical challenge in identifying the causal effect of the shift to variable pricing is that the teams' switch may not be exogenous. Specifically, teams' decisions to switch to variable pricing decisions may be influenced by factors such as the demographic characteristics of the teams' locations (see the first column of Table 5 in Appendix B for the list of all factors). Hence, a simple comparison of ticket sales between games of teams which switched to variable pricing, and those of teams which did not switch, may be misleading. We address this challenge with several identification strategies.

5.1. Empirical Strategy: Difference-in-Differences with Propensity Score Weighting

We can use a Difference-in-Differences (DiD) identification strategy (Angrist and Pischke 2008) to estimate the main effects of the switch to variable pricing, since only a subset of teams switched immediately after the NFL allowed variable pricing (prior to the beginning of the 2014 season). Specifically, we estimate the effects of variable pricing tactics on the variables of interest by

---

[7] NFL hosted six NFL International Series games outside the US across 2012-2014. The Buffalo Bills hosted one game at the Roger Center in Toronto during each season in 2012 to 2013. Finally, the 2014 regular season game between the New York Jets and Buffalo Bills was played in Detroit due to a snow storm in Buffalo.

[8] A similar analysis on the teams which did not switch to variable pricing also shows non-significant changes, 92.94 ($p > .10$) for the stadium capacity and 2.21 ($p > .10$) for the average ticket prices.

comparing games of teams that switched to variable pricing (i.e., treatment group) and games of teams that did not (i.e., control group), before and after the pricing strategy switch (i.e., treatment). The list of teams in the treatment and control groups can be seen in Table 4 of Appendix A.

To implement a DiD approach, there should be no unobserved, time-varying, and game-specific factors that are correlated with both the shift to variable pricing and the three factors we study: primary market sales, number of ticket listings in the resale market, and the resale market get-in price. To address this potential concern, we include (i) some important control variables such as home teams' location-specific demographic factors (e.g., population, median income, income diversity, and ethnicity diversity) and team performance factors (e.g., home team's previous season performance and home team's weekly odds of winning the Super Bowl), (ii) team fixed effects for unobserved home team-specific time-invariant factors (e.g., fans' preference for watching their teams' games in the stadium), (iii) opponent fixed effects for unobserved away team-specific time-invariant factors (e.g., fans' preference for supporting their team by attending away games), and (iv) NFL week and yearly fixed effects for unobserved time trends (e.g., changes in importance of games as the season progresses).

We implement the DiD with propensity score weighting to further reduce concerns about potential endogeneity (see Bell et al. 2017 for a similar approach). In principle, the goal is to decrease the possibility for unobservable differences between the treated and control games by reducing imbalances of observable characteristics between the two groups. We choose a widely used observation weighting approach, Propensity Score Weighting, from a family of Propensity-score-based methods, first introduced by Rosenbaum and Rubin (1983). The propensity score is defined as the probability that a unit receives the treatment, conditional on its observed characteristics. Propensity-score-based-methods try to eliminate potential biases in comparison of the treated and control units.

The propensity score weighting is one such method, which uses propensity scores as sampling weights to make the two groups comparable with respect to their observable factors (see Rosenbaum 1987, Hirano and Imbens 2001, and Hirano et al. 2003). This method avoids undesirable loss of subjects (Guo and Fraser 2010), and fits well to our setting because of the small number of the NFL teams. Following Hirano and Imbens (2001), we define the sampling weights as $w(T,x) = \frac{T}{\hat{\pi}(x)} + \frac{1-T}{1-\hat{\pi}(x)}$ where T indicates a team game being treated and $\hat{\pi}(x)$ is the estimated probability of being treated based on the observable factors. In our study, we calculated these weights at the team-level. We then incorporate these weights into our estimation procedure. In our propensity score weighting, we utilize (i) mean and standard deviation of attendance, average ticket price, and team performance for the 2013 season, (ii) the preseason Super Bowl odds, stadium capacity, number of championships for the 2014 season, and (iii) demographic factors of teams' hometowns (median income, Gini coefficient for income, Gini coefficient for ethnicity, and population), which could all be determinants of a team's decision to switch to variable pricing in 2014. We use logistic regression to calculate the propensity scores (see Table 5 in Appendix B for the propensity score estimation results). We conduct t-tests to see whether teams in treatment and control groups are comparable.

Following Guo and Fraser (2010), we compare the characteristics of two groups based on the averages of the weighted characteristics. Table 6 in Appendix B shows the averages for each factor in the treatment and control groups and the resulting t-tests of their comparisons. These tests show no statistically significant evidence to reject that the two groups have the same averages at the 10% significance level. The results of the t-tests show that the games of the teams in the treatment and control groups are comparable in terms of our key variables. Hence, we can identify the average effect of the switch to variable pricing by utilizing the variation in the treatment status across the weighted observations.

5.2. The Effect of the Switch to Variable Pricing on Primary Market Sales

We next estimate the average effect of the switch to variable pricing on primary market ticket sales, $PMSales$. Our unit of analysis is at the team i - home game g level. We identify the effect using log link:

$$ln(PMSales_{ig}) = \alpha_i + \beta\, VP_{ig} + W_{ig} + Y_{ig} + O_{ig} + X'_{ig}\,\gamma + \varepsilon_{ig}, \qquad (1)$$

where the indicator variable VP_{ig} is 1 if team i has already switched to variable pricing during its home game g, and 0 otherwise. Team fixed effects, α_i, capture time-invariant unobserved factors of each team. The set of indicator variables W_{ig} represents 17 different NFL regular season weeks for team i's game g. The indicator variable representing the week in which a team i's home game g' takes place is 1, and all other indicator variables are 0. For instance, if a team's first home game

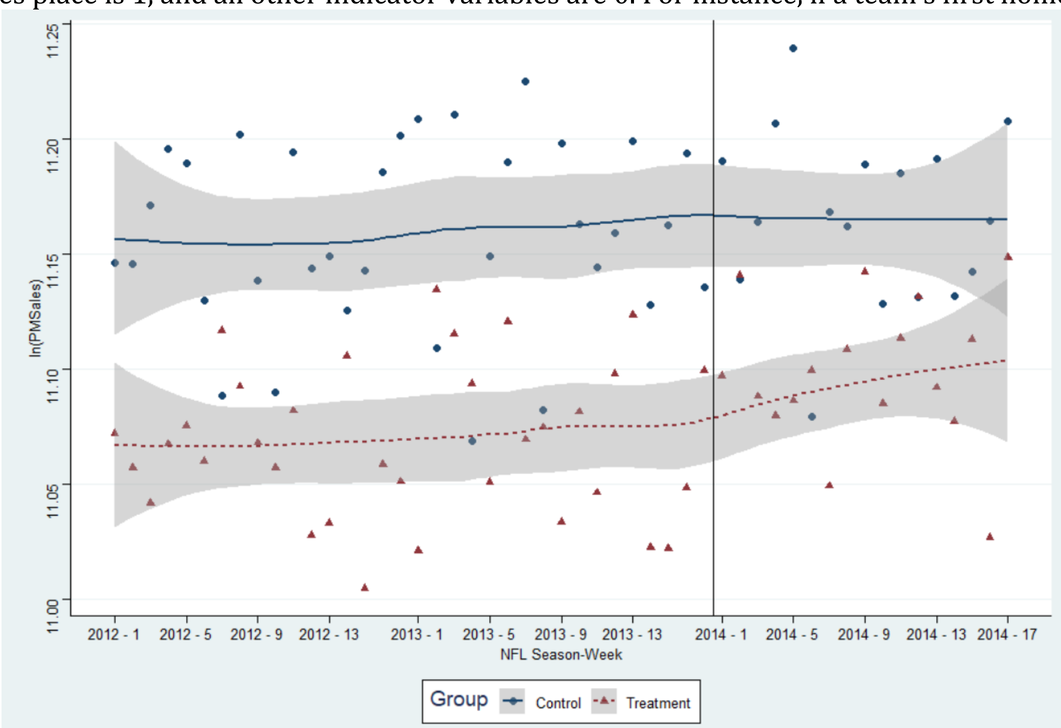

Figure 2. Impact of Variable Pricing on Primary Market Sales: A Graphical Analysis

is in the second NFL week, the corresponding dummy in the vector for the second NFL week will take 1, while others take 0. Y_{ig} is the set of indicator variables which represent the three seasons in 2012-2014. The indicator variable representing the season in which a team i's home game g's takes place is 1, and all other indicator variables are 0. O_{ig} is the set of indicator variables which represent opponent team fixed effects. The vector X_{ig} consists of team- and game-related control variables. It includes a team's hometown demographic factors: median income, population, the natural logarithm of the Gini coefficient of income, and the natural logarithm of the Gini coefficient of ethnicity. X_{ig} also includes the yearly average ticket price set by the team within the season, the percentage change in the average ticket price compared to the previous season, the yearly seating capacity of team i's home stadium, the team's previous year performance, and preseason Vegas odds for the team to win the Super Bowl. Finally, we also include teams' corresponding weekly Vegas odds of winning the Super Bowl in X_{ig}. Our coefficient of interest in Equation 1 is β. Its estimated value gives us the average effect of the switch to variable pricing on primary market sales in percentages through $100 \times (\exp(\hat{\beta}) - 1)$.

Identification Check. We perform an identification check to examine whether our empirical strategy can extract the causal effect of the shift to variable pricing prior to the estimation of Equation 1. Figure 2 shows the average primary market sales for the treated and control games in our observation period. The smooth trend lines (obtained using a Locally Weighted Smoothing approach) fitted to each group's observations show almost parallel lines prior to the switch to variable pricing in the 2014 season.

To validate our parallel trend observation, we run a linear regression with a slight modification to

Table 2. Impact of Variable Pricing on Primary Market Sales and Possible Mechanisms

Variables	(1)	(2)	(3)	(4)	(5)
VP	0.0291**	0.0362***	0.0126	0.0211*	0.0125
	(0.0101)	(0.0104)	(0.0087)	(0.0094)	(0.0100)
VP × % Change in Average Ticket Price		-0.0065***	-0.0020	-0.0021	0.0021
		(0.0009)	(0.0019)	(0.0018)	(0.0017)
VP × Median Income			-0.0288***	-0.0278***	-0.0237**
			(0.0080)	(0.0079)	(0.0086)
VP × Income Diversity			1.1194***	1.1378***	1.4075***
			(0.2830)	(0.2762)	(0.3211)
VP × Attractiveness				-0.0221*	-0.0212*
				(0.0109)	(0.0108)
Other Demographic Interactions	No	No	No	No	Yes
Team FE	Yes	Yes	Yes	Yes	Yes
NFL Regular Season Week FE	Yes	Yes	Yes	Yes	Yes
NFL Season FE	Yes	Yes	Yes	Yes	Yes
Opponent Team FE	Yes	Yes	Yes	Yes	Yes
Team- and Game-Related Controls	Yes	Yes	Yes	Yes	Yes
No. of obs.	688	688	688	688	688
Adjusted R^2	82.13	82.99	83.51	83.61	83.65

Notes. * $p < .05$, ** $p < .01$, *** $p < .001$. Dependent variable is the natural logarithm of primary market sales volume ($ln(PMSales)$). Robust standard errors in parentheses for specifications.

Equation 1 for the pre-treatment period (2012-2013) as follows:

$$ln(PMSales_{ig}) = \alpha_i + \lambda_1 t_{ig} + \lambda_2 Treated_i \times t_{ig} + O_{ig} + X'_{ig}\,\gamma + \xi_{ig}, \qquad (2)$$

where the indicator variable $Treated_i$ is 1 if team i is one of the teams which switched to variable pricing in 2014 switched to variable pricing in 2014, and 0 otherwise. t_{ig} is the NFL regular season week numbers of team i's game g for 2012-2013 seasons, where t_{ig} = {1, ..., 34}.[9] The coefficient of interest in this regression is λ_2 as it will indicate if the weekly sales trend differs across the treatment and control groups prior to the 2014 season. Estimation results of Equation 2 show that there is no statistically significant difference between the weekly sales trends across the treated and control groups prior to the 2014 season ($\hat{\lambda}_2$ = 0.0002 with p > .10). This identification check supports our empirical strategy although, as with any quasi-experimental analysis, no identification test is entirely conclusive.

Main Effect on Primary Market Sales. The first column of Table 2 presents the estimated effect of the switch from fixed to variable pricing on primary market ticket sales using Equation 1. It shows that the average effect of the switch to variable pricing on primary market ticket sales of a game is positive ($\hat{\beta}$ = 0.0291) and statistically significant (p < .01). This effect amounts to a 2.95% (i.e., 100 × (exp(0.0291) − 1)) increase in primary market ticket sales in response to a switch to variable pricing by teams. This result shows that a switch to variable pricing benefits the teams' primary market ticket sales.

To strengthen the causal interpretation of our main result, we also perform a falsification test as suggested in Goldfarb and Tucker (2014). This test helps to eliminate any remaining concerns about endogeneity. This can be done by using all the pre-treatment seasons and divide them into two halves, namely before and after the placebo switch to variable pricing. In particular, we re-estimate our main specification to determine if there is a treatment group effect in a season when no teams could switch to variable pricing, i.e., in the 2013 season. Then, we test whether the coefficient for a placebo switch to variable pricing is significant. Finding a significant effect would imply that unobservable differences correlated with switches to variable pricing are biasing our estimated main effect. We report the result from this falsification exercise in Table 7 within Appendix C. The results show that the estimate for the placebo switch to variable pricing variable is not statistically significant (0.0104, p > .10).

We also test if our finding aligns with the basic inverse demand-price relationship. Specifically, we explore how our result differs between teams that choose to increase or decrease their average ticket price across all the games between seasons. To assess this question, we add an interaction term of VP and the percentage change in average ticket price across seasons to Equation 1. Column (2) in Table 2 provides the coefficient estimates for the new specification. The coefficient of the new interaction term is negative and statistically significant (-0.0065, p < .001). This implies that the positive effect of the shift to variable pricing is attenuated by an increase in the average ticket price across the games relative to the previous season.

6. Mechanism

We next investigate various mechanisms through which the switch to variable pricing affects the primary market ticket sales. We argue that the switch to variable pricing influences consumer demand through the attenuation of uncertainty in predicting the popularity of a game: quality-

[9] There is a total of 34 weeks in 2012 and 2013 regular seasons.

signaling by price differentiation. Specifically, a team's switch to variable pricing can indicate which games are expected to be attractive and unattractive with the new high and low prices, respectively, relative to its old fixed pricing strategy. The switch to variable pricing is expected to be more effective for price-sensitive customers who are uncertain about the quality of a game and usually defer their purchases to the resale market to avoid paying unnecessarily high prices for unpopular games in advance. Hence, if quality-signaling is the underlying mechanism, we anticipate a larger increase in less attractive games' primary market ticket sales. The other mechanism behind an increase in sales for any game (popular or unpopular) could be a team's decision to decrease the average price across high- and low-priced games in the new season after the switch to variable pricing. We already controlled for this mechanism and shared the corresponding result in §5.2.

To establish that a quality-signaling mechanism is at work, we document the following supplemental evidence. First, we provide evidence that the switch to variable pricing has a more positive effect in towns with lower income levels and higher income diversity. Second, we show that the switch to variable pricing has a more positive sales effect on less attractive games. These mechanism checks highlight the circumstances in which a switch to variable pricing is more effective, and "help make causal identification more convincing" (Goldfarb and Tucker 2014).

6.1. Shift to Variable Pricing Has a More Positive Impact for Towns with Lower Income Levels and Higher Income Diversity

Prior literature indicates that consumers with lower income have a higher likelihood of searching for lower prices and end up paying lower prices on average (Goldman and Johansson 1978). Siegfried and Peterson (2000) found that consumers of sporting events tickets had a median income 84% above the national median income. With the switch to variable pricing, the unattractive games are now priced lower. Naturally, lower income customers, who would not normally purchase a ticket, can now purchase tickets from the primary market. Therefore, we expect that the impact of the shift to variable pricing will be more positive in towns with lower income levels and higher income diversity. To examine this conjecture, we use the following specification:

$$\begin{aligned} ln\left(PMSales_{ig}\right) = \alpha_i + \beta\, VP_{ig} + \theta\, VP_{ig} \times \%\, Change\ in\ Average\ Ticket\ Price_{ig} \\ +\delta_1\, VP_{ig} \times Median\ Income_{ig} + \delta_2\, VP_{ig} \times Income\ Diversity_{ig} \\ +W_{ig} + Y_{ig} + O_{ig} + X'_{ig}\,\gamma + \varepsilon_{ig}, \end{aligned} \tag{3}$$

where the variables $Median\ Income_{ig}$ and $Income\ Diversity_{ig}$ are the yearly demographic characteristics for the hometown of each team i. The parameters of interest in this specification are δ_1 and δ_2. δ_1 measures the heterogeneous impact of the shift to variable pricing on primary market ticket sales in terms of the median household income for a given team's home game. δ_2 measures the heterogeneous effect of the switch in terms of the household income diversity for a given team's home game. The new specification has the same fixed effects and control variables as those defined in Equation 1. Column (3) of Table 2 shows the coefficient estimates for the new specification. The negative and statistically significant coefficient estimate of the $VP_{ig} \times Median\ Income_{ig}$ ($\hat{\delta}_1 = -0.0288$, p < .001) suggests that the increase in primary market ticket sales in response to the shift to variable pricing is greater in a team hometown with lower income relative to a hometown with higher income. In addition, the positive and statistically significant coefficient estimate of the $VP_{ig} \times Income\ Diversity_{ig}$ ($\hat{\delta}_2$ = 1.1194, p < .001) suggests that the increase in primary market ticket sales in response to the switch to variable pricing is greater in a team home-town with higher income diversity relative to one with lower income diversity. These results show that with variable pricing, primary market ticket sales indeed increased more in team hometowns with lower income levels and higher income diversity.

6.2. Shift to Variable Pricing Has a More Positive Impact for Less Attractive Games

Under the fixed pricing strategy, customers who are uncertain about the quality of a game usually defer their purchases to the resale market to avoid paying unnecessarily high prices for unattractive games in advance. Therefore, the benefit of the switch to variable pricing is greater for less attractive games as price differentiation will clearly display a team's expectations about which games will be more or less attractive. As a result, we expect that the positive effect of the switch to variable pricing will be more positive for less attractive games.

In order to explore how the impact of variable pricing changes based on the attractiveness of a game, we first need to discern between attractive and unattractive games. However, this is not a trivial task, since all teams in the 2012 and 2013 seasons, and 17 out of 32 teams in the 2014 season used a fixed pricing strategy. One solution would be to look at game attendance; however, it may be problematic due to potential real-time effects. For example, a bad performance by the team or bad weather may pull the attendance numbers down for a game which was perceived as attractive at the beginning of the season.

To solve this issue, we build a Machine Learning technique using historical attendance and detailed NFL game-, team-, and hometown-data to identify attractive games for the 2012 and 2013 seasons, and also the 2014 season for teams which didn't switch to variable pricing. Our test-run using 2014 data of teams which switched to variable pricing show that our algorithm correctly classifies 85.4% of the games which were selected as high-priced games by these teams. We provide details of our approach in Appendix D.

We define an indicator variable $Attractiveness_{ig}$ to be 1 for those games which are identified as popular by our algorithm for the 2012-2013 seasons or high-priced games of teams which switched to variable pricing in the 2014 season, and 0 otherwise. To formally assess our earlier prediction regarding the differing effect of the switch to variable pricing based on the attractiveness of the game, we estimate the following specification:

$$\begin{aligned} ln\left(PMSales_{ig}\right) = \alpha_i + \beta\, VP_{ig} + \theta\, VP_{ig} \times \%\ Change\ in\ Average\ Ticket\ Price_{ig} \\ +\delta_1\, VP_{ig} \times Median\ Income_{ig} + \delta_2\, VP_{ig} \times Income\ Diversity_{ig} \\ +\eta\, VP_{ig} \times Attractiveness_{ig} + W_{ig} + Y_{ig} + O_{ig} + X'_{ig}\,\gamma + \varepsilon_{ig} \qquad (4) \end{aligned}$$

where η gives the heterogeneous impact of the switch to variable pricing on primary market ticket sales in terms of the more attractive games for a given team's home games. The fixed effects and control variables are kept the same as those in Equation 1. Column (4) in Table 2 provides the coefficient estimates for this specification. The coefficient estimate of the $VP_{ig} \times Attractiveness_{ig}$

is negative and statistically significant (η = -0.0221, p < .05). This result indicates that the gain in primary market ticket sales in response to the switch to variable pricing is more substantial for less attractive games.

We also compute the F-statistic to evaluate the null hypothesis that $\beta = |\eta|$. The test fails to reject the null (F = .01 with p > .10), indicating that primary market sales for more attractive games do not change significantly after the shift to variable pricing. Importantly, although there is a price increase for more popular games after the shift to variable pricing, this does not appear to have a negative effect on sales for popular games.

This is the first indication that the option-value effect compensates for the negative effect of price increase on demand and that customers continue to purchase tickets for attractive games in advance knowing that they will be able to sell their tickets later at a higher price. We will supplement this conjecture later by analyzing the customers' choice of prices in the resale market in Section 7.

6.3. Interactions with Other Demographics

We also control for additional demographic interactions with VP to reduce any potential moderating effects of other demographic variables on the relationship between switch to variable pricing and primary market ticket sales. In particular, we include the interactions of population and ethnic diversity with the indicator for a switch to variable pricing (VP) in Equation 4, and report the estimates for our key interactions in Column (5) of Table 2. Our previous findings stay robust to the incorporation of these additional interactions.

6.4. Additional Robustness Check

All NFL teams except for the New Orleans Saints eventually implemented some version of variable pricing after our observation period. Having only one remaining team may indicate that some unobservable differences have prevented this team from switching to variable pricing. To address potential biases that may arise from this one control team, we re-estimate our specifications on Table 2 by excluding New Orleans Saints's home games from our sample. Table 8 within Appendix C show the estimation results. Our previous findings stay robust to the exclusion of the New Orleans Saints from our sample.

7. Effect of the Shift to Variable Pricing on Customer Activity in the Resale Market

Our results show that the switch to variable pricing leads to an increase in primary market ticket sales for teams via the quality-signaling mechanism. This indicates that, with variable pricing, there are more customers with the potential to list their tickets in the resale market. This shift can have unexpected consequences due to the intertwined primary and resale market dynamics (as discussed earlier with Figure 1). In particular, having more customers who could list their tickets in the resale market also means that there is a potential for more competition from the resale market. However, this additional competition could only be harmful if the switch to variable pricing has led to a decrease of prices in the resale market.

In the subsections that follow, we show that the teams' switch to variable pricing did not lead to negative effects through resale markets by documenting two additional evidences. First, we provide evidence that the switch to variable pricing indeed resulted in more ticket listings for less attractive games in the resale market. Second, we show that the lowest ticket listing price (i.e., get-in price) in the resale market did not change significantly for less attractive games after the switch to variable pricing. These checks aid in better understanding the effect of the switch to variable pricing on teams through resale markets.

7.1. The Effect of the Shift to Variable Pricing on the Number of Ticket Listings in the Resale Market

We first estimate the heterogeneous effect of the shift to variable pricing on the number of ticket listings in the resale market based on the attractiveness of the games. The structure of the specification is very similar to Equation 1, except for the replacement of the dependent variable with the number of ticket listings in the resale market and the inclusion of the interaction of VP_{ig} and $Attractiveness_{ig}$ variable. We use the following specification:

$$RMListings_{ig} = \alpha_i^{Listings} + \beta^{Listings}\, VP_{ig} + \eta^{Listings}\, VP_{ig} \times Attractiveness_{ig} \\ + W_{ig} + Y_{ig} + O_{ig} + X'_{ig}\, \gamma^{Listings} + \varepsilon_{ig}^{Listings}, \qquad (5)$$

where $RMListings_{ig}$ is the number of ticket listings in the resale market for team i's home game g.

Table 3. Impact of Variable Pricing on the Number of Ticket Listings and the Minimum Ticket Price Listed in the Resale Market

Variables	$\boldsymbol{RMListings}$ (1)	$\boldsymbol{ln(MinResalePrice)}$ (2)
VP	645.56*	-0.0784
	(294.40)	(0.0542)
VP × Attractiveness	-1,080.28**	0.2370***
	(346.32)	(0.0704)
Team FE	Yes	Yes
NFL Regular Season Week FE	Yes	Yes
NFL Season FE	Yes	Yes
Opponent Team FE	Yes	Yes
Team- and Game-Related Controls	Yes	Yes
No. of obs.	688	544
Adjusted R^2	84.60	85.80

Notes. * $p<.05$, ** $p<.01$, *** $p<.001$. Robust standard errors in parentheses for specifications. The specification in the second column includes the natural logarithm of the primary market minimum ticket price as opposed to the average ticket price included in the specification of the first column.

Team fixed effects are now captured by $\alpha_i^{Listings}$. The vector of NFL week fixed effects (W_{ig}) and yearly fixed effects (Y_{ig}, the vector of opponent team fixed effects (O_{ig}), and the vector of control variables (X_{ig}) stay the same as in Equation 1.[10] Our interest in this specification are $\beta^{Listings}$ and

[10] Since our resale market data come from the period right before the start of the season, preseason and weekly Vegas odds for a team to win the Super Bowl are the same.

$\eta^{Listings}$. Prior to estimation of this specification, we also performed an identification check by running a linear regression using Equation 2 with $RMListings_{ig}$ as the dependent variable. The details of this analysis can be found in Appendix E. The estimation results show that there is no statistically significant difference between the weekly listing trends across the treated and control groups prior to the 2014 season.

The first column of Table 3 summarizes the estimated heterogeneous effect of the switch from fixed to variable pricing on the number of ticket listings in the resale market based on the attractiveness of games using Equation 5. The positive and statistically significant coefficient estimate of VP_{ig} ($\hat{\beta}^{Listings}$ = 645.46, $p < .05$) suggest that the number of ticket listings in the resale market increased after the switch to variable pricing for less attractive games. This result indicates that teams faced a higher competition from the resale market for their less attractive games after their switch to variable pricing.

For more attractive games, the negative and statistically significant coefficient estimate of the interaction $VP_{ig} \times Attractiveness_{ig}$ ($\eta^{Listings}$ = $-1,080.28$, $p < .01$) shows that the number of ticket listings in the resale market for more attractive games went down by 435 (calculated using $645.46 - 1,080.28$) for those teams that switched to variable pricing. Hence, the competition from the resale market for more attractive games went down for those teams that switched from fixed to variable pricing.

7.2. The Effect of the Shift to Variable Pricing on the Minimum Ticket Listing Price in the Resale Market

We next assess if the increased competition from the resale market for less attractive games is a threat for those teams that switched to variable pricing. To answer this question, we estimate the heterogeneous effect of the shift to variable pricing on the minimum ticket listing price in the resale market based on the attractiveness of the games. The structure of the specification is the same as Equation 5 except for the replacement of the dependent variable with the natural logarithm of the minimum ticket listing price in the resale market ($ln(MinResalePrice)$) as follows:

$$\begin{aligned}\ln(MinResalePrice)_{ig} = \alpha_i^{MinRP} + \beta^{MinRP}\, VP_{ig} + \eta^{MinRP}\, VP_{ig} \times Attractiveness_{ig} \\ + W_{ig} + Y_{ig} + O_{ig} + X'^{MinRP}_{ig}\, \gamma^{MinRP} + \varepsilon_{ig}^{MinRP}. \qquad (6)\end{aligned}$$

In this specification, α_i^{MinRP} captures the team fixed effects. As before, W_{ig} is the vector of NFL week fixed effects and Y_{ig} is the vector of year fixed effects. O_{ig} is the vector of opponent team fixed effects. Following Sweeting (2012), we use primary market prices as a control for exploring the changes in resale market prices by replacing the yearly average primary market ticket price in X'_{ig} with the natural logarithm of the each game's primary market minimum ticket price to get X'^{MinRP}_{ig}. Since the primary market minimum ticket prices for 144 games in our sample are not available, we conduct this analysis with the remaining 544 games. We also performed an identification check for this new specification by running a linear regression using Equation 2 with $\ln(MinResalePrice)_{ig}$ as the dependent variable. We provide the details of this analysis in Appendix E. The results of the identification check show that there is no statistically significant difference between the weekly minimum resale price trends across the treated and control groups prior to the 2014 season.

Column (2) of Table 3 provides the estimated heterogeneous effect of the switch to variable pricing on the minimum ticket listing prices in the resale market based on the attractiveness of games using Equation 6. The nonsignificant coefficient estimate of VP_{ig} ($\hat{\beta}^{MinRP}$ = −0.0784, $p > .10$) indicates that minimum ticket listing prices for less attractive games did not change in the resale market for teams that switched to variable pricing. We can conclude that the increase in the number of ticket listings in the resale market for the less attractive games does not seem to be a threat for the teams that switched to variable pricing. In the end, customers did not list their tickets for these games at lower prices after teams switched to variable pricing.

For the more attractive games of teams that switched to variable pricing, the positive and statistically significant coefficient estimate of the interaction $VP_{ig} \times Attractiveness_{ig}$ (η^{MinRP} = 0.2370, $p < .001$) shows that the minimum ticket listing prices in the resale market increased. This increase in prices also supports our earlier finding which shows decreased competition due to the lower number of listings in the resale market for attractive games in §7.1.

Overall, our results show that the switch from fixed to variable pricing for some NFL teams in 2014 did not lead to cannibalization from resale markets. Although we find an increased number of ticket listings for less attractive games in the resale market, without a corresponding decrease in resale ticket prices, this is not a threat for the teams that switched to variable pricing. In the end, switching to variable pricing was a win-win for the teams, because it increased the primary market sales for the less attractive games while avoiding cannibalization from the resale market. Moreover, recall that increases in the primary market prices for more attractive games did not result in a decrease in the primary market sales for these games. This shows that customers continued to purchase tickets for the attractive games from the primary market, even after a price increase for these games. These customers also listed tickets in the resale market at higher prices. This indicates that the option-value effect (Bennett et al. 2015) kicked in after teams displayed the popularity of some games through higher prices in the primary market.

8. Conclusion

In an age when many sports and arts organizations are considering a switch to variable pricing from the traditional fixed pricing strategy, it is crucial to understand whether and where variable pricing policies are effective in boosting the primary market sales and alleviating cannibalization from the resale market. Using quasi-experimental data from the NFL, this study empirically examines the effectiveness of a switch to variable pricing.

Our study provides several key findings. First, teams that switched to variable pricing sold 2.95% additional tickets per game through the primary market. Second, in line with the quality-signaling mechanism for price-sensitive customers, variable pricing led to higher primary market sales for (i) games in team hometowns with lower income levels and higher income diversity, and (ii) less attractive games. Variable pricing did not change the sales for more attractive games. Third, following the implementation of variable pricing, the number of ticket listings in the resale market went up for less attractive games and down for more attractive games. Finally, the minimum ticket listing price in the resale market did not change for less attractive games, but went up for more attractive games.

8.1. Key Implications

Our key findings have important implications for both managers and policymakers. First, it is not clear whether the positive effect of variable pricing on ticket sales for less attractive games and the insignificant effect for more attractive games will lead to revenue benefits. The NFL does not share any revenue information at the game level, therefore we use a hypothetical NFL team based on average team-related observations in the 2012-2013 seasons to estimate revenue figures. Suppose that this hypothetical team sells an average of 67,566 tickets for unattractive games and an average of 68,859 tickets for attractive games without variable pricing. By switching to variable pricing, the team management sets the average ticket prices of five unattractive games 12% cheaper than the fixed price, and sets the average ticket prices of three attractive games 20% more expensive than the fixed price (therefore, keeping the total price the same). Using the specification in Equation 4, we find the change in ticket sales for each game, and calculate the revenues with and without variable pricing. This analysis shows that the revenue impact of a switch to variable pricing is 1.26% for this hypothetical team.

Second, we find that variable pricing is more effective in team hometowns with lower income and higher income diversity. We repeat the same revenue analysis for teams with a half standard deviation higher and lower median income level and income heterogeneity values than their means. Our analysis shows that the revenue benefits of variable pricing can be up to 5% for a hypothetical NFL team with a hometown that has a lower median income level and a higher income heterogeneity. This implies that taking demographic heterogeneity into account while making pricing decisions can help teams attain better revenues. Furthermore, our finding that variable pricing increases demand more for team hometowns with lower income and higher income diversity supports the criticism that traditional fixed pricing strategies favor the customers with higher income. Therefore, policymakers can encourage variable pricing for organizations as a way to address this fairness issue in markets.

Third, our analysis of the customers' ticket selling decisions in the resale market also sheds light on the effect of variable pricing on the primary and resale market dynamics. Our findings reveal that a thorough evaluation of the effects of variable pricing on primary market sales requires an analysis of its effects on resale market activities. Although our findings (higher sales for unattractive games and no change in sales for attractive games) suggest greater performance, the increase in the number of ticket listings in the resale market for unattractive games can lead to higher cannibalization of primary market demand later in the season. We find that the minimum ticket listing prices on the resale market did not change for unattractive games after the switch to variable pricing. This is in opposition to a common but untested criticism that variable pricing runs counter to other strategies designed to eliminate cannibalization from resale markets.

Fourth, our finding that variable pricing had an insignificant effect on primary market sales for attractive games implies that the price increase did not lead to a decrease in demand for attractive games. This result highlights a lack of price sensitivity for attractive games. As such, managers can utilize higher prices for these games to further increase their revenues from attractive games without fear of backlash from the market. In addition, the increased minimum listing prices for attractive games in the resale market after variable pricing indicates that customers purchased tickets in the hope of selling their tickets later at a higher price (i.e., the option-value effect). This could be a concern for managers, as it may encourage scalping in the primary market. However, we find that the number of ticket listings in the resale market decreased after variable pricing. This runs counter to another untested criticism that variable pricing encourages scalping behavior in the primary market.

8.2. Limitations and Future Research

In this study, we examine one of the recently favored pricing tactics, variable pricing. Even though we run a set of robustness checks, as in any study relying on observational data, there is room for further assessment of our results. More research on the effectiveness of other types of pricing tactics would enhance our understanding of which pricing strategies work best in settings with both primary and resale markets. We also hope that future studies will shed further light on the effect of variable pricing as organizations in different contexts implement variable pricing, since we were only able to focus on a single sports league due to the extensive data collection required. Finally, a structural analysis of the consumers' utilities from different ticket choices and welfare implications of variable pricing are other potential directions for future research.

References

[1] Akçay Y, Natarajan HP, Xu SH (2010) Joint dynamic pricing of multiple perishable products under consumer choice. *Management Science* 56(8):1345–1361.

[2] Allon G, Bassamboo A (2011) Buying from the babbling retailer? The impact of availability information on customer behavior. *Management Science* 57(4):713–726.

[3] Anderson SP, Ginsburgh VA (1994) Price discrimination via second-hand markets. *European Economic Review* 38(1):23–44.

[4] Angrist JD, Pischke JS (2008) *Mostly harmless econometrics: An empiricist's companion* (Princeton University Press).

[5] Arslan HA, Easley R, Wang R, Yilmaz O (2019) Data-driven sports ticket pricing for multiple sales channels and heterogeneous customers.
Available at SSRN: https://ssrn.com/abstract=3447206

[6] Bachman R (2018) College Football's growing problem: Empty seats. *The Wall Street Journal.*
Accessed: July 28th, 2019. https://on.wsj.com/2PlwYZB

[7] Bagwell K, Riordan MH (1991) High and declining prices signal product quality. *The American Economic Review* 81(1):224–239.

[8] Bell DR, Gallino S, Moreno A (2017) Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Science* 64(4):1629–1651.

[9] Bennett VM, Seamans R, Zhu F (2015) Cannibalization and option value effects of secondary markets: Evidence from the US concert industry. *Strategic Management Journal* 6(11):1599–1614.

[10] Brown M (2011) How sports attendance figures speak lies. *Forbes.*
Accessed: July 28th, 2019. https://bit.ly/2Kft1EW

[11] Cachon GP, Daniels KM, Lobel R (2017) The role of surge pricing on a service platform with self-scheduling capacity. *Manufacturing & Service Operations Management* 19(3):368–384.
[12] Cachon GP, Feldman P (2017) Is advance selling desirable with competition? *Marketing Science* 36(2):214– 231.
[13] Chen J, Esteban S, Shum (2013) When do secondary markets harm firms? *American Economic Review* 103(7):2911-2934.
[14] Cohen P, Hahn R, Hall J, Levitt S, Metcalfe R (2016) Using big data to estimate consumer surplus: The case of Uber.
Available at NBER Working Paper Series: https://www.nber.org/papers/w22627.
[15] Connolly M, Krueger AB (2018) The secondary market for concert tickets: Theory and evidence. *International Journal of Music Business Research* 7(2):6–51.
[16] Courty P, Pagliero M (2012) The impact of price discrimination on revenue: Evidence from the concert industry. *The Review of Economics and Statistics* 94(1):359–369.
[17] Cui R, Shin H (2018) Sharing aggregate inventory information with customers: Strategic cross-selling and shortage reduction. *Management Science* 64(1):381–400.
[18] Cui R, Zhang DJ, Bassamboo A (2019) Learning from inventory availability information: Field evidence from Amazon. *Management Science* 65(3):1216–1235.
[19] Cui Y, Duenyas I, Sahin O (2014) Should event organizers prevent resale of tickets? *Management Science* 60(9):2160–2179.
[20] Drayer J, Shapiro SL, Lee S (2012) Dynamic ticket pricing in sport: An agenda for research and practice. Sport Marketing Quarterly 21(3):184-194.
[21] Engber D (2017) Could variable ticket pricing save the movies? *Slate.*
Accessed: May 29, 2019. https://bit.ly/2ztjCH8.
[22] Feldman P, Li J, Tsai HT (2018) Welfare implications of congestion pricing: Evidence from SFpark.
Available at SSRN: https://ssrn.com/abstract=2834019.
[23] Fisher E (2014) NFL warms up to variable pricing. *Sports Business Journal.*
Accessed: June 22nd, 2019. https://bit.ly/1km7yXs.
[24] Gale IL, Holmes TJ (1993) Advance-purchase discounts and monopoly allocation of capacity. *American Economic Review* 83(1):135–146.
[25] Gallego G, Sahin O (2010) Revenue management with partially refundable fares. *Operations Research* 58(4):817-833.
[26] Gallino S, Moreno A (2014) Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Science* 60(6):1434–1451.
[27] Gaur V, Park YH (2007) Asymmetric consumer learning and inventory competition. *Management Science* 53(2):227-240.
[28] Goldfarb A, Tucker CE (2014) Conducting research with quasi-experiments: A guide for marketers.
Available at SSRN: https://ssrn.com/abstract=2420920.
[29] Goldman A, Johansson JK (1978) Determinants for search of lower prices: An empirical assessment of the economics of information theory. *Journal of Consumer Research* 5(3):176–

186.
[30] Guo S, Fraser MW (2010) *Propensity score analysis: Statistical Methods and Applications* (SAGE).
[31] Hendel I, Lizzeri A (1999) Interfering with secondary markets. *The RAND Journal of Economics* 30(1):1–21.
[32] Hirano K, Imbens GW (2001) Estimation of causal effects using propensity score weighting: An application to data on right heart catheterization. *Health Services and Outcomes Research Methodology* 2(3-4):259– 278.
[33] Hirano K, Imbens GW, Ridder G (2003) Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica* 71(4):1161–1189.
[34] Kline DB (2019) How Disney World is using pricing to spread out its crowds. *USA Today.* Accessed: May 28, 2019. https://bit.ly/2Xes0CC.
[35] Kok AG, Shang K, Yucel S (2018) Impact of electricity pricing policies on renewable energy investments and carbon emissions. *Management Science* 64(1):131–148.
[36] Leslie P (2004) Price discrimination in Broadway theater. *The RAND Journal of Economics* 35(3):520–541.
[37] Leslie P, Sorensen A (2014) Resale and rent-seeking: An application to ticket markets. *The Review of Economic Studies* 81(1):266–300.
[38] Lewis M, Wang Y, Wu C (2019) Season ticket buyer value and the secondary market options. *Marketing Science* Forthcoming.
[39] Phillips R (2017) The NFL is seriously concerned with empty stadiums. *The Big Lead.* Accessed: June 22nd, 2019. https://bit.ly/2WYg9r2.
[40] Phillips RL (2005) Variable pricing. *Pricing and Revenue Optimization*, 106–111 (Stanford University Press), 1st edition.
[41] Pigou AC (1932) *The Economics of Welfare* (Macmillan), 4th edition.
[42] Preuss H (2007) The conceptualisation and measurement of mega sport event legacies. *Journal of Sports & Tourism* 12(3-4):207–227.
[43] Rishe P (2014) Pricing insanity at March Madness: Exploring the causes of secondary price markups at the 2013 Final Four. *International Journal of Sport & Society* 4(2).
[44] Rosen S, Rosenfield AM (1997) Ticket pricing. *Journal of Law and Economics* 40(2):351–376.
[45] Rosenbaum PR (1987) Model-based direct adjustment. Journal of the American Statistical Association 82(398):387-394.
[46] Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41–55.
[47] Siegfried JJ, Peterson T (2000) Who is sitting in the stands? The income levels of sports fans. Kern WS, ed.,*The Economics of Sports*, 51–74 (Kalamazoo, MI: W.E. Upjohn Institute for Employment Research).
[48] Stevenson S (2019) Dallas Cowboys are raising ticket prices in 2019. *Star-Telegram.* Accessed: May 28, 2019. https://bit.ly/2ww5M2V.
[49] Su (2010) Optimal pricing with speculators and strategic consumers. *Management Science* 56(1):25–40.

[50] Suslow VY (1986) Estimating monopoly behavior with competitive recycling: An application to Alcoa. *The RAND Journal of Economics* 17(3):389–403.
[51] Sweeting A (2012) Dynamic pricing behavior in perishable goods markets: Evidence from secondary markets for Major League Baseball tickets. *Journal of Political Economy* 120(6):1133–1172.
[52] Talluri KT, van Ryzin GJ (2004) *The Theory and Practice of Revenue Management* (Kluwer Academic Publishers).
[53] Tereyagoglu N, Fader PS, Veeraraghavan S (2018) Multiattribute loss aversion and reference dependence: Evidence from the performing arts industry. *Management Science* 64(1):421–436.
[54] Transchel S (2017) Inventory management under price-based and stockout-based substitution. *European Journal of Operational Research* 262(3):996–1008.
[55] Trefis Team (2017) Stubhub to drive eBay's revenue growth, profits could remain low. *Forbes.* Accessed: June 26, 2019. https://bit.ly/31Yf1rw.
[56] Vickrey W (1971) Responsive pricing of public utility services. *The Bell Journal of Economics and Management Science* 2(1):337–346.
[57] Xu JJ, Fader PS, Veeraraghavan S (2019) Designing and evaluating dynamic pricing policies for Major League Baseball tickets. *Manufacturing & Service Operations Management* 21(1):121–138.
[58] Zhao W, Zheng YS (2000) Optimal dynamic pricing for perishable assets with nonhomogeneous demand. *Management Science* 46(3):375–388.
[59] Zou T, Jiang B (2018) Can musicians and fans benefit when a primary ticket platform controls the resale market? Theory and evidence.
Available at SSRN: https://ssrn.com/abstract=3203293.

Appendix A: Treatment and Control Groups

Table 4. List of Teams in the Treatment and Control Groups

Treatment Group	Control Group
Arizona Cardinals	Baltimore Ravens
Atlanta Falcons	Carolina Panthers
Buffalo Bills	Chicago Bears
Detroit Lions	Cincinnati Bengals
Jacksonville Jaguars	Cleveland Browns
Kansas City Chiefs	Dallas Cowboys
Miami Dolphins	Denver Broncos
Minnesota Vikings	Green Bay Packers
New England Patriots	Houston Texans
Pittsburgh Steelers	Indianapolis Colts
Saint Louis Rams	New Orleans Saints
San Diego Chargers	New York Giants
San Francisco 49ers	New York Jets
Seattle Seahawks	Oakland Raiders
Tennessee Titans	Philadelphia Eagles
	Tampa Bay Buccaneers
	Washington Redskins

Appendix B: Propensity Score Weighting

Table 5. Logistic Regression Results for Propensity Score Weighting

Variable	Coef.	SE
Attendance SD (2013)	2.6284	7.3343
AverageTicketPrice (2013)	0.0158	0.0403
PreviousSeasonPerformance (2014)	0.3941	0.9720
PreseasonSuperBowlOdds (2014)	-0.4720	16.8340
StadiumCapacity (2014)	-0.0001	0.0001
Championships (2014)	-0.3498	0.2299
MedianIncome	-0.8882	0.9165
ln(*GiniIncome*)	-16.4987	17.5588
ln(*GiniEthnicity*)	-2.0924	2.3862
Population	0.1285	0.2254
N	29	
LL	-15.14	

Note. Attendance_Mean(2013) is dropped because of collinearity.

Table 6. Comparison of Matching Characteristics after Propensity Score Weighting

Variables	Treated	Control	Difference	Weighted *p*-value
Attendance_Mean (2013)	11.07	11.16	-0.09	0.183
Attendance_SD (2013)	11.16	11.21	-0.05	0.814
AverageTicketPrice (2013)	76.28	85.84	-9.56	0.712
PreviousSeasonPerformance (2014)	1.58	1.35	0.23	0.926
PreseasonSuperBowlOdds (2014)	4.71	4.62	0.09	0.904
StadiumCapacity (2014)	69,293.33	71,994.71	-2,701.38	0.722
Championships (2014)	1.83	3.65	-1.82	0.651
MedianIncome	5.44	6.11	-0.67	0.361
ln(*GiniIncome*)	-0.77	-0.75	-0.02	0.588
ln(*GiniEthnicity*)	-0.74	-0.62	-0.13	0.618
Population (in millions)	2.94	5.69	-2.75	0.723

Note. As suggested in Guo and Fraser (2010), we ran weighted OLS regressions to find weighted *p*-values. In these regressions, our covariates become dependent variable and dichotomous treatment variable is the single independent variable.

Appendix C: Additional Robustness Checks

Table 7. Robustness Check: Falsification Test

Variables	(1)
Placebo *VP*	0.0104
	(0.1060)
Team FE	Yes
NFL Regular Season Week FE	Yes
NFL Season FE	Yes
Opponent Team FE	Yes
Team- and Game-Related Controls FE	Yes
No. of obs.	460
Adjusted R^2	86.78

Notes. * $p < .05$, ** $p < .01$, *** $p < .001$. Robust standard errors in parentheses for specifications. Dependent variable is the natural logarithm of primary market sales volume. Placebo *VP* is the indicator variable which takes 1 for all the home games of the treatment group in the 2013 season, 0 otherwise.

Table 8. Robustness Check: Models excluding the New Orleans Saints

Variables	(1)	(2)	(3)	(4)	(5)
VP	0.0297**	0.0362***	0.0129	0.0217*	0.0128
	(0.0103)	(0.0105)	(0.0087)	(0.0095)	(0.0101)
VP × % Change in Average Ticket Price		-0.0064***	-0.0020	-0.0021	0.0022
		(0.0018)	(0.0019)	(0.0019)	(0.0018)
VP × Median Income			-0.0286***	-0.0276***	-0.0232**
			(0.0081)	(0.0080)	(0.0097)
VP × Income Diversity			1.1136***	1.1327***	1.4150***
			(0.2849)	(0.2777)	(0.3283)
VP × Attractiveness				-0.0229*	-0.0220*
				(0.0110)	(0.0109)
Other Demographic Interactions	No	No	No	No	Yes
Team FE	Yes	Yes	Yes	Yes	Yes
NFL Regular Season Week FE	Yes	Yes	Yes	Yes	Yes
NFL Season FE	Yes	Yes	Yes	Yes	Yes
Opponent Team FE	Yes	Yes	Yes	Yes	Yes
Team- and Game-Related Controls	Yes	Yes	Yes	Yes	Yes
No. of obs.	664	664	664	664	664
Adjusted R^2	81.93	82.77	83.29	83.41	83.45

Notes. * $p < .05$, ** $p < .01$, *** $p < .001$. Dependent variable is the natural logarithm of primary market sales volume ($ln(PMSales)$). The estimations are run without including the games of New Orleans Saints. Robust standard errors in parentheses for specifications.

Appendix D: Discerning between Attractive and Unattractive Games

Our supervised Machine Learning algorithm learns the *best* mapping function that turns a set of predictors into game attendance using the following steps (see Figure 3 for a sketch of the attractive game identification process).

1. The algorithm uses linear regression to understand the determinants of game attendance in 2012-2013 based on several independent predictors, such as home and opponent team, team performance etc.

2. In order to forecast the perceived attractiveness (i.e., "attractiveness index") for each game at the beginning of the season (instead of the actual attendance), the algorithm uses the regression results in Step 1, excluding the real-time effects (e.g., team's up-to-date performance).

3. The algorithm repeats steps (1) and (2) for different time periods, 2011-2013 and 2010-2013.

4. The algorithm compares the prediction performance of three regressions on the "attractiveness" observed in the real data, i.e., "high-priced games" chosen by the teams which switched to variable pricing in 2014 using (i) logit model, (ii) probit model, and (iii) binary classification test[11], and chooses the best time period for the use of historical data. Table 9 presents the regression results of the best-performing regression model, which uses only 2012 and 2013 season's data. We note that this model outperforms others and does exceptionally well with a True Positive Rate of 85.4%.

5. Using the "attractiveness index" of best-performing regression model, the algorithm lists 2014 season home games of each team that did not switch to variable pricing in descending order and picks the top three teams as *synthetic* "attractive games".[12]

6. The algorithm picks *synthetic* "attractive games" for all teams in 2012 and 2013 seasons using a similar Machine Learning strategy with a historical data length of two years.

To demonstrate our approach, we share an example here from San Diego Chargers. Figure 4 shows the observed and predicted (excluding real-time effects) paid attendance for San Diego Chargers for the 2014 season. The San Diego Chargers selected Denver Broncos, New England

[11] For this test, the algorithm lists the 2014 home games of each team that switched to variable pricing in descending order based on the "attractiveness index." For a team which selected *n* "high-priced games" with the variable pricing, the algorithm compares the top *n*-games in the "attractiveness index" list with the selected "high-priced games."

[12] Note that most NFL teams that switched to variable pricing selected three games as "high-priced games". As a robustness check, we repeat the analyses including the Attractiveness in the paper with top-2 and top-4 teams scenarios. Our results hold.

Patriots, and Seattle Seahawks as their "high-priced games," which is identical with what the algorithm predicts.

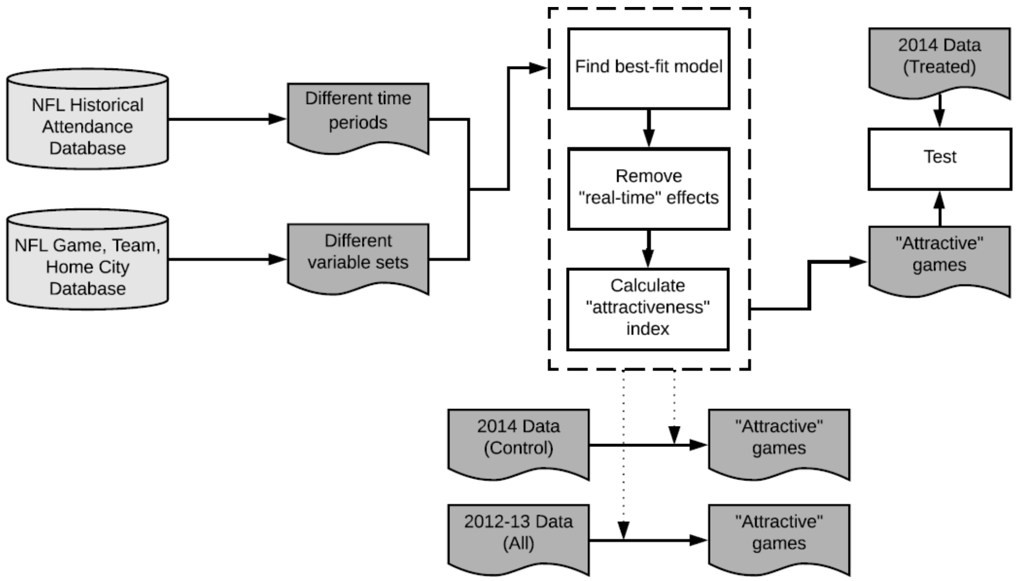

Figure 3. Process for Identification of Attractive Games

Table 9. Regression Results for Game Attendance in 2012-2013

Variable	**Coef.**	**SE.**
Weekly Super Bowl Odds	0.0721*	0.0343
Preseason Super Bowl Odds	-0.0382	0.0916
Previous Season Performance	0.0050	0.0031
Opponent Previous Season Performance	0.0019	0.0038
Opponent Preseason Super Bowl Odds	0.1775+	0.1061
Opening Line	-0.0014+	0.0007
Division Game	0.0077+	0.0044
First Home Game	0.0208	0.0167
NFL Kick-off Game	0.0013	0.0132
Thanksgiving	0.0066	0.0147
Team FE	Yes	
NFL Regular Season Week FE	Yes	
NFL Season FE	Yes	
Opponent Team FE	Yes	

Note. + $p<0.1$, * $p<0.05$.

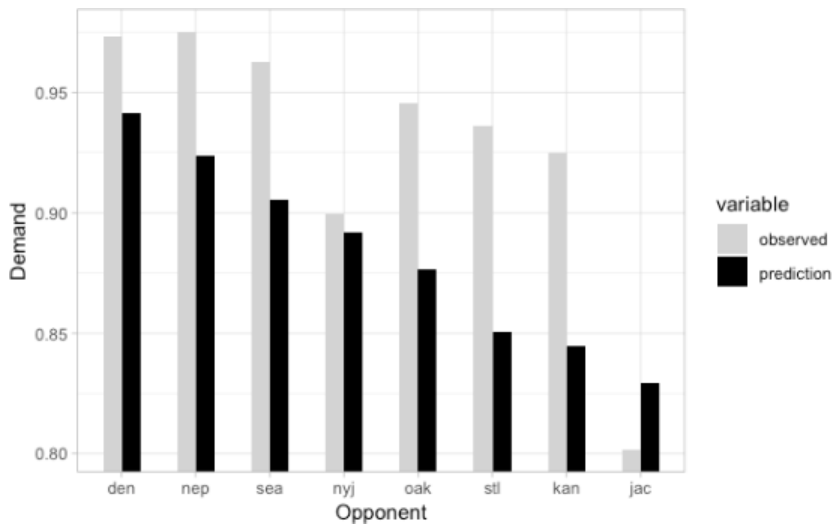

Figure 4. San Diego Chargers (2014)

Appendix E: Identification Check for Resale Market Analysis

E.1. Checking Parallel Trends for the Number of Ticket Listings in the Resale Market

We estimate a slight modification of Equation 2 for the pre-treatment period by replacing the dependent variable with $RMListings_{ig}$. The coefficient of interest in this regression, $\lambda_2^{Listings}$, shows if the weekly ticket listings trend is different across the treated and control groups prior to 2014 season. Estimation results show that there is not a statistically significant difference between the weekly listing trends across the treated and control groups prior to 2014 season ($\hat{\lambda}_2^{Listings}$ = 5.7979, $p > .10$). This finding confirms parallel trends for weekly ticket listings across the treated and control groups.

E.2. Checking Parallel Trends for the Number of the Lowest Ticket Price in the Resale Market

We again estimate a slight modification of Equation 2 for the pre-treatment period by replacing the dependent variable with $ln(MinResalePrice)_{ig}$. The coefficient of interest in this regression, λ_2^{MinRP}, shows if the weekly minimum resale price trend is different across the treated and control groups prior to 2014 season. Estimation results show that there is not a statistically significant difference between the weekly minimum resale price trends across the treated and control groups prior to 2014 season ($\hat{\lambda}_2^{MinRP}$ = -0.0009, $p > .10$). This finding confirms parallel trends for weekly ticket listings across the treated and control groups.