IMPACT OF PLAYER QUALITY ON DEMAND IN MAJOR LEAGUE SOCCER: A STUDY OF STAR AND INTERNATIONAL PLAYER EFFECT ON MATCH ATTENDANCE

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ABSTRACT

This paper examines how one of the determinants of demand for sports—player quality—influenced Major League Soccer during the seasons from 2004 to 2014. The impact is evaluated by estimating star and international players effect on match attendance. A star player is defined by their base salary, by their performance, and by their popularity. An international player is defined by his nationality. In terms of star effect, this study finds evidence that star players defined only by salary information exhibit a positive relationship on match attendance; especially, a top-10 paid player appears to produce a statistically significant increase in attendance. This study also finds evidence that there is a superstar externality in Major League Soccer but only in terms of salary information. In addition, it is obvious that an international player has a positive impact on match attendance and African and Asian players in particular are statistically significant. The implication of this study is favorable regarding the enactment of the Designated Player rule in 2007, which has allowed the league to better compete in the international soccer markets.

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CHAPTER ONE

INTRODUCTION

Major League Soccer (MLS) is the highest level professional soccer league, sanctioned by the U.S. Soccer federation, in both the United States and Canada. The league was founded in 1993 as part of the United States' successful bid to host the 1994 FIFA World Cup. After a preparation period, MLS's inaugural season took place in 1996 with 10 teams. By 2015, its twentieth anniversary, the league had expanded to 20 teams, with 17 teams from the U.S. and 3 from Canada. The league is divided into the Eastern and Western Conferences and each team plays 34 games in an unbalanced schedule. This means that a team has 24 matches against teams within its conference and 10 matches against teams outside its conference. The team with the best record is awarded the Supporter's Shield. The regular season runs from March to October. The postseason has twelve teams competing in the MLS Cup Playoffs through November and December, culminating in the championship game, the MLS Cup. Midway through the season, teams break for the annual All-Star Game, a friendly game between the league's finest players or a major club from a different league such as Manchester United in England and Bayern Munich in Germany.

1.1 Growth and Uniqueness

Hosting the 1994 World Cup and the 1999 Women's World Cup, and rebooting the soccer league in the U.S. after the demise of the North American Soccer League (NASL) in 1984 were highly estimated as decisive moments that allowed people in the U.S. to keep up with soccer, rather than American football. Despite successful features in its inaugural season, during its first few years the MLS went through financial and operational struggles. Average attendance declined for four consecutive seasons (see Table 1.1), and the league lost millions of dollars on its massive initial investment. Teams played in mostly empty gridirons far too big for soccer; repeated rule changes upset long-standing fans; the quality of play was low, and so forth (Jewell, 2015). According to a BBC report (Slater, 2015), this has been referred to as the grim first five years for the MLS. As a result, two teams (Miami Fusion and Tampa Bay Mutiny) folded before the 2002 season. Both fans and players considered MLS an unappealing soccer league. Most of the best American players such as Landon Donovan and Clint Dempsey left for European leagues at an early age.

Though mired in controversy, the league was showing signs of growth in terms of its popularity and quality. One indicator of measuring its popularity and growth might be its rise in match attendance. On one hand, since 2011, MLS has surpassed the National Hockey League (NHL) and the National Basketball League (NBA) and ranks third after the National Football League (NFL) and Major League Baseball (MLB; Bryant, 2015). One thing that has made this happen is because the club owners have built soccer-specific stadiums so the quality of viewing has increased[1]. By the 2015 season, the average attendance had reached 21,574 per game. Though this does not indicate that MLS has become greater than NBA and NHL, it does mean that the league is growing in terms or its popularity.

On the other hand, according to a Forbes report (Smith, 2015), the average MLS team is

[1] A soccer-specific stadium typically has amenities, dimensions and scale suitable for soccer in North America, including a scoreboard, video screen, luxury suites and possibly a roof. By the 2015 season, there are 14 out of 20 MLS teams played games in soccer specific stadiums.

now worth $157 million, up 52% compared to two year ago. Also, new eight-year TV contracts with ESPN, FOX Sports, and Univision signed before the 2014 season brought the league revenue of $90 million per year higher than the $18 million per year from the previous contract (Bissonnette, 2014). Consistently televising games on Friday and Sunday at a fixed time every week has allowed MLS to have the continuity of broadcasting games and making fans think of MLS as a partner for their weekend. By doing so, MLS has attracted more fans to become loyal fans and the league has now become profitable. The league is not only raising its match attendance but also capitalizing on its local markets.

Unlike the European soccer leagues and even other major leagues in the U.S. as well, the success and growth of the league are attributable to the uniqueness of its system and structure, according to a comment from Don Garber, the league's commissioner. He believes that this excites people and gets them involved in watching the game (Slater, 2015). First, the league operates as a single entity in which each team is owned and controlled by the league as a whole. Each club has investor-operators, who are shareholders in the league controlling their teams as owners do in other leagues. However, the league manages everything from players' contracts and merchandizing to sponsorships. Second, similar to other U.S. major leagues, it is a closed system, meaning that there is no promotion or relegation system. Instead, it has the playoffs, for which the top 12 teams overall (without distinction of the conference) qualify based on their regular season records. This allows twelfth-ranked team to reverse the league standings and get a chance to win the title of the MLS Cup. The Portland Timbers, for example, a fifth-ranked team won the MLS Cup in 2015. Third, the league has a salary cap and the draft system to keep costs down and keep the league being competitive among franchises (competitive balance). Though each MLS team has its own youth academy, the MLS SuperDraft is an annual event as popular as the league itself.

1.2 Improvement in Quality of Playing

The league has had some indicators that it has been successful in the last three or four years. Its objective now is to be considered among the world's best soccer leagues by 2022. The league plans to expand to 22 teams in 2017, ultimately to 23 teams in 2018. It is impossible, however, to reach its goals without expanding the fan base since those fans are ultimately the core driver behind almost every league revenue stream, from gate receipts and merchandizing to sponsorship and TV deals (Smith, 2015). Though MLS has attained the position as the third-ranked sport league in the U.S. in terms of the average match attendance, the league revenue is still substantially small compared to those other leagues[2]. Thus, it is still largely dependent on match attendance. Therefore, it is critical to expand the fan base and in order to do so, the league has to improve the quality of play by 1) changing the rules so that they appeal more to fans, 2) moving franchise to match local demand, 3) realigning conference to stimulate regional rivalries, and so forth (Jewell, 2015).

Arguably the most immediate way to improve the quality of play is to improve the quality of players. MLS has been trying to be an attractive league to some widely known superstars. Historically, however, contracts for international superstars have failed to lead to widespread interest in the U.S. Before the MLS, there was the North American Soccer League (NASL) formed

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2 The MLS' 2014 revenue of roughly $461 million pales in comparison to that of the other four major leagues, the NFL, MLB, NBA and NHL, which in 2014 respectively earned $11.2 billion, $9 billion, $4.8 billion and $3.7 billion.

in 1968. The NASL also tried to retain its popularity by accepting some world-renowned soccer players such as Pelé, Johan Cruyff, Gerd Müller, and Eusébio. But the league was abolished in 1984 despite the presence of those players due to the massive popularity of the four major leagues (NFL, MLB, NBA, and NHL) in the U.S. Before the 2007 season, MLS finally instituted the Designated Player (DP) rule, part of the salary cap regulation, when they first accepted David Beckham into the league. It allows each franchise to sign players that would normally be considered outside the team's salary cap, allowing MLS teams to compete for star players in the international soccer market.

The acceptance of David Beckham and other DP players after him into the league was estimated as one of the important reasons that MLS has gained nationwide popularity. The eventual influence by Beckham on the league extended well beyond his performances on the pitch. His good looks, his talent for self-promotion, and most of all his elevated career in soccer had a great impact on demand for the league from gate receipts and merchandizing to sponsorship and endorsement. He was not only one superstar among the whole MLS players but also was an ambassador and his awareness was instrumental in helping popularize the league in a country where it traditionally struggled for mainstream attention. Since his first season, a few studies on his or other designated players' impact on the MLS have been conducted and these found evidence that the impact was significant (see Lawson et al., 2008; Parrish, 2013; Jewell, 2015).

On the other hand, some oppose the influx of high-profile foreign players into the league. Some argue that the majority of those players are already past their prime when they decide to come to the league. Thus, the exorbitant salaries paid to those players might cause a huge income disparity among players and might raise the question of whether the league is suffering from short-termism in its thinking. For example, the total amount of salaries that Robbie Keane and Steven Gerrard received in 2015 were enough to cover 55% of the total LA Galaxy's payroll. This is unrelated to the fairness which the Americans first consider traditionally or why the league imposed the salary cap rule. Additionally, some insist that the ultimate success of MLS will depend on the contribution of homegrown players. The transfusion of some young talented players from abroad (e.g., Sebastian Giovinco and Giovani Dos Santos), these critics claim, will impede the development of domestic youngsters in the long run. This is in line with some policies that the European soccer leagues has recently imposed restricting the eligibility of international players for playing in order to encourage homegrown younger domestic players to equip their competitiveness in soccer markets.

Therefore, the league's policy of accepting high-profile players to popularize soccer in America is still controversial. On one hand, it is expected to increase demand for MLS in terms of many indicators such as match attendance, merchandizing, and sponsorship revenues. On the other hand, it might, in the long run, impede the development of domestic youngsters and the league itself. MLS is growing but is still dependent on game-day revenues attributable to the sustainable popularity by the foundation of a sizable fan base. Given this, the next question American soccer fans should be asked is whether they feel comfortable with the influx of foreign star players into the league. Therefore, it is necessary to examine the preference of American soccer fans for the presence of some high-profile players and estimate, empirically, the actual impact of those players on demand for the MLS.

1.3 Purpose of the Study

The purpose of this study is to examine the preference of American soccer fans for high-profile players by estimating the effect those players have on match attendance. Such an estimate, formed by analyzing data from 2004 to 2014 season, could serve as one of the proxies of measuring demand for the MLS based on the Consumer Theory in Economics. Especially in this study, there are two main streams of analyzing the effect on match attendance: star player effect on game-day attendance and the impact of foreign-born player on attendance.

Player quality determines the playing quality, one of the determinants of demand for sports (Borland & Macdonald, 2003). There have been plenty of previous empirical studies on the effect of a superstar on match attendance in major professional sports. The results, however, are mixed (see Berri et al., 2004; Berri & Schmidt, 2006; Brandes et al., 2008; Franck & Nüesch, 2012; Hausman & Leonard, 1997; Jane, 2014; Jewell, 2015; Lawson et al., 2008; LeFeuvre et al., 2013; Mullin & Dunn, 2002; Rivers & DeSchriver, 2002). There exists some subjectivity issues of defining superstar status because the results are very dependent on the definition of star players and the identification of star players under the definition. Additionally, there has been no literature on the MLS introducing and utilizing generalizable analysis of the relationship between star players and match attendance. Given these issues, therefore, one purpose of this study is to first define somewhat objective definitions of identifying superstar status. This study refers to similar concepts used by Jane (2014) in the NBA. Under this setting, this study expects to find a positive relationship between star player and match attendance in the MLS.

Some superstar literature found evidence that there is superstar externality meaning that star players attract more fans to stadium on the road. However, most of the literature on superstar externality were using NBA cases. Even though there were some studies on superstar externality in the MLS (Lawson et al., 2002; Jewell, 2015), those studies aimed to find superstar externality by certain players, not the whole group of star players. Furthermore, to find David Beckham's externality, Lawson et al. (2002) investigated his effect not on match attendance but on ticket sales. Thus, the second purpose of this study regarding star player effect is to examine superstar externality in terms of match attendance in the MLS using analysis generalizable to the whole group of players.

The previous research about the effect of international players on demand for sports relates to the concept of customer discrimination (Khan, 2000). It is normally analyzed by the relationship of matching between team and population demographics. The previous research found evidence that matching a team's racial composition with the population of the market area covered by the team increased attendance (see Burdekin & Idson, 1991; Burdekin et al., 2005; Hoang & Rascher, 1999). However, there have been no similar studies conducted to find the effect of the mere presence of international players on match attendance. Thus, this study aims to discern how MLS fans respond in terms of match attendance to the presence of the international players in the league. Furthermore, to see the individual group effect compared to that of domestic players, players are divided into confederations under the FIFA structure and will be so examined.

The rest of this article is organized as follows. The next chapter, Chapter 2, introduces and reviews, some previous studies about superstar and customer discrimination. Chapter 3 introduces data, model, and methodologies. Chapter 4 discusses the regression results. And the last chapter offers a summary of the study's main conclusions.

CHAPTER TWO

LITERATURE REVIEW

2. 1 Determinants of Demand for Sports

The study of demand for sports is based on rudimentary consumer theory in Economics. However, sports markets are different from those discussed in Economics. In his classic Sport Economics article, Neale (1964) first discussed the peculiar nature of the demand side of professional sporting markets—the joint nature of sports production. In other words, the core product, which is game itself, is jointly produced by two or more teams (or individuals). In an economic sense, it is necessary for firms to reduce competition so they can gain more profit. Similarly, in the professional sports world, the objective of the team owner or manager is either to maximize profits or to maximize the team's winning percentage.

However, in a sports context, it is imperative to understand the essence of demand in terms of attendance, that is, "fan interest (or preference)" (Borland & Macdonald, 2003). In a standard consumer theory model, a representative consumer is assumed to choose a consumption bundle to maximize utility, subject to a budget constraint. Thus, consumers have to make a rational decision and there should be a trade-off between affordable consumption bundles. In sports, fans decide whether they attend the game or not based not only on the typical economic factors (e.g., ticket price, income, and the presence of substitutes or complements) but also on the preference for their favorite team (e.g., the quality of team, individual players, and stadium). Therefore, in an analysis of a professional sports market, one of the most important empirical issues is understanding the nature and determinants of demand (Borland & Macdonald, 2003).

The first empirical study about the determinants of demand for sports was by Noll (1974). He analyzed the seasonal data of four American sport leagues (baseball, basketball, football, and ice hockey) from the late 1960s to the early 1970s. The explanatory variables for attendance were economic factors (e.g., ticket price). Thereafter, there have been plenty of empirical studies analyzing the effect of the determinants on demand for sports.

Schofield (1983) first reviewed 17 previous articles about the determinants of attendance. Since then, Borland and Macdonald (2003), after reviewing the previous literature based on the consumer theory model, introduced five main categories of determinants of demand for sports. The categories are as follows: 1. consumer preferences (e.g., habit and age of clubs); 2. economic factors (e.g., admission price, travel costs, income, and market size); 3. quality of viewing (e.g., quality of facilities, weather, and timing of contest); 4. characteristics of the sporting contest (e.g., uncertainty of outcome, competing teams, and high-quality of skills); and 5. supply capacity (e.g., stadium size). Thus, player effect—star and international player effect in this study—falls in the fourth category, the characteristics of the sporting contest.

2.2 Star Players on Demand

The first systematic study of the effect of star players on attendance was also conducted by Noll (1974). He found that what had a considerable impact on home attendance for the National Basketball Association (NBA), American Basketball Association, and Major League Baseball was the number of star players a team had (Jane, 2014). Since then, a point of controversy has been determining whether stars drive demand by their remarkable talent (Rosen, 1981) or by their higher popularity (Adler, 1985). Based on these theoretical works, the studies on the effect of high-profile players are tied in the literature on “superstar” (Jewell, 2015). There are two main streams analyzing the star effect—the relationship between superstar status and salary (Franck & Nüesch, 2012; Kuethe & Motamed, 2010; Lucifero & Simmons, 2003) and the influence of the superstar effect on attendance (Berri & Schmidt, 2006; Berri et al., 2004; Brandes et al., 2008; Hausman & Leonard, 1997; Lawson et al., 2008; LeFeuvre et al, 2013; Jane, 2014; Jewell, 2015). This study, as with most of the previous research, is related to the latter stream.

2.2.1 Star Effect on Attendance

Recent superstar literature concedes that the presence of star players increase demand in terms of either the match attendance or consumption in general. Theoretically, star players in professional sports can help generate wins, and they can lead to more fans. Mixed, however, are the empirical results of the major professional sport leagues from the previous superstar literature (see Berri & Schmidt, 2006; Berri et al., 2004; Brandes et al., 2008; Franck & Nüesch, 2012; Mullin & Dunn, 2002; Hausman & Leonard, 1997; Jane, 2014; Jewell, 2015; Lawson et al., 2008; LeFeuvre et al., 2013; Rivers & DeSchriver, 2002).

By analyzing all NBA local and national television ratings as well as match attendance, Hausman and Leonard (1997) empirically investigated the superstar effect on team revenue in professional basketball. They found that the presence of a certain superstars, such as Larry Bird or Michael Jordan, had a significant impact on television ratings as well as match attendance and a substantial positive impact on club revenues. Additionally, for example, they estimated the value of Michael Jordan to the other NBA teams to be approximately US$53 million, giving rise to the concept of externality. However, they did not analyze whether the star’s performance and/or popularity increased team revenues.

Berri et al. (2004) and Berri and Schmidt (2006) extended the work of Hausman and Leonard. Berri et al. investigated a two-sided relationship: the relationship between match attendance and team performance, and the team's mere employment of star players in the NBA. They found that although star power was statistically significant, stars did not have significant effects on gate receipts, which is one of the major revenue sources for an NBA team. They concluded this was because of performance on the court, not star popularity. At the end of their research, they mentioned superstar externality suggesting that the true power of the star may lie in his ability to enhance attendance on the road.

Berri and Schmidt extended the study of Berri et al. using road attendance in the NBA and found evidence of superstar externality. They estimated that a top-25 All-Star player attracted an average of 4,353 fans; this is fewer than the 9,846 attracted by their win production. Thus, they pointed out that showmanship could not replace actual on-court performance.

Most recently, Jane (2014) investigated the relationship between the star effect and match attendance in the NBA using five different definitions of star players based on performance, salary, and popularity. Using a censored regression technique, he found evidence that the appearance of stars increases home and road game attendance and there was a positive superstar externality of game attendance.

In Major League Baseball (MLB), Mullin and Dunn (2002) defined "star quality" as the residuals in the model of baseball card prices based on performance statistics. They found evidence that star quality brought fans to the stadium and impacted team revenues in a significant way that went beyond pure on-field productivity. However, Rivers and DeSchriver (2002) found that if a star player did not contribute to an increase in the team's on-field performance, the player had little influence on attendance. The presence of players who were stars in the previous season (e.g., MVP and Cy Young Awards candidates) had no significant relationship to attendance. Also the presence of players who were stars within the last five years (e.g., MVP and Cy Young voting from the last five years) had no significant relationship to attendance. Thus, they suggested that MLB teams should invest their payroll evenly across the 25-man roster rather than on one or two star players.

2.2.2 Star Effect in Soccer

There has also been a stream of superstar literature regarding soccer (Brandes et al., 2008; Franck & Nüesch, 2012; Jewell, 2015; Lawson et al., 2008; LeFeuvre et al., 2013; Lucifora & Simmons, 2002; Parrish, 2013). Concerning match attendance for all clubs in Bundes Liga, the highest German soccer league, Brandes et al. (2008) studied the relationship between a nationwide superstar, whose market value was in the top 2% quantile of the league's distribution, and a local hero, the most valuable player of a particular team that had no superstar. They found that while national superstars enhance attendance both at home and on the road, the star attraction of local heroes was limited to home games. In addition, superstars attracted fans by their outstanding field performances, whereas local heroes facilitated fan support through mere popularity.

There are relatively few superstar studies of Major League Soccer (MLS) because its history in the United States has thus far been rather brief. Moreover, in contrast to the literature using a general group of players under a certain definition of superstar, the majority of studies on MLS estimated the effect of a certain player or group of players under the Designated Player rule (DP rule). Since the 2007 season when MLS accepted David Beckham, the DP rule has been part of the salary cap regulation; it allows MLS teams to compete for star players in the international soccer market, with the league paying $400,000 of the contract.

Lawson et al. (2008) simply investigated the effect David Beckham's American presence had on MLS ticket sales for the 2007 season. They found that Beckham had a large effect on MLS attendance and generated enough additional revenue each game played to cover the entire $400,000 league contribution to his salary. Since each team played 15 road games in 2007 season, their estimate of the Beckham effect suggested that the MLS's DP Rule should allow the league to pay up to $6,000,000 ($= \$400{,}000 \times 15$) of Beckham's salary in order to fully internalize the superstar externality. In the second part of his research, Parrish (2013) studied the relationship between the number of the DPs present at a given game and match attendance and found a statistically significant difference of attendance between matches without DPs and matches with multiple DPs as well as matches with 1 DP and with multiple DPs.

Jewell (2015) empirically analyzed the effect of the DP rule on demand. He took seven DPs, referring to them as marquee players. They were the following: David Beckham, Cuauhtémoc Blanco, Thierry Henry, Tim Cahill, Torsten Frings, Robbie Keane, and Rafael Márquez. He found that only Beckham and Blanco drove up attendance during their MLS careers, though this effect tended to diminish over time. For David Beckham, all of his base salary was likely covered by game-day attendance alone. Jewell also found that there were superstar externalities.

2.3 International Players on Demand

Becker (1971) identified three potential forms of discrimination in labor market: employer, co-worker including the relationship between supervisors and supervisees, and customer discrimination. Under certain conditions, discriminating employers will be eliminated by the non-discriminators, and coworker discrimination will result in equal pay for equal work (Khan, 2000). However, customer discrimination is different because it is sometimes rewarded by the market when employers pay more money to workers whom customers prefer. This suggests that competitive forces are less likely to eliminate customer-based discrimination. The second part of this study, therefore, is to investigate customer discrimination in the MLS by simply examining the effect of international players on match attendance, since the sports industry is a customer-based service sector (Kahn, 2000).

Earlier studies on customer discrimination examined how the inclusion of black players affected demand after 1947 when Jackie Robinson first broke the color line. Since then, there have been different dimensions of customer racial discrimination examined in professional sports: by looking at the price of player cards (e.g., Fort & Gill 2000; Longley et al. 2008; McGarrity et al. 1999; Nardinelli & Simon 1990; Primm et al. 2010; Stone & Warren 1999), Hall of Fame and All-Star voting (e.g., Depken & Ford 2006; Desser et al. 1999; Hanssen & Andersen 1999), television ratings (e.g., Kanazawa & Funk, 2001; Nüesch & Franck 2009), and game attendance (e.g., Hersch 2010; Tainsky & Winfree 2010). This study uses game attendance in the MLS.

2.3.1 Customer Discrimination in Sports

Customer prejudice in baseball was first examined in the 1970s, but the results were somewhat ambiguous. Gwartney and Haworth (1974) studied the decade after integration and found that black players on a club increased annual team attendance, though the results were insignificant. They estimated that a black player on the roster raised about 16,000 – 29,000 fans per year to the team. They explained this because the inclusion of black player on a club increased team quality and thus, independent of winning, brought additional customers to the stadium (Tainsky & Winfree, 2010). Desser et al. (1999) tested for the existence of discrimination in Hall of Fame voting against African American and Latin American players using players' lifetime performance statistics and career achievements. Though the magnitude of discrimination was small, they found evidence that there was a racial bias both in the nominating process and votes among baseball writers.

In basketball, Burdekin and Idson (1991) scrutinized NBA fans of the 1980s and found that the racial composition of NBA teams was positively correlated with the racial composition of their metropolitan markets. They also found that attendance was positively affected by a close match between the racial composition of the team and the area. Subsequent research has found similar evidence; attendance increased when a team's racial composition matched the population of the market area (Burdekin et al., 2005; Hoang & Rascher, 1999). One exception to this was study by McCormick and Tollison (2001), who found no relationship.

2.3.2 Customer Discrimination in Soccer

There have been only a few previous studies on customer discrimination in professional soccer and most of those examined European soccer leagues. No such study has been conducted with the MLS. Szymanski (2000) tested for salary discrimination based on race in the English soccer league, assuming that if there is a competitive market for players, a team's payroll would reflect their productivity and hence the performance of the team. However, if teams with an above-average proportion of black players outperformed teams with a below-average proportion of black players, discrimination could exist. In this regard, he found significant evidence of discrimination. In contrast, Preston and Szymanski (2000) found no evidence of a link between the selection of black players and match attendance and suggested that customer discrimination is not responsible for the racial influence on the relationship between wage expenditure and team performance.

To distinguish foreign players from local players, the information of country-of-origin has to be utilized as an important input effect on consumer behavior (Tainsky & Winfree, 2010). Pedace (2008) proposed a market test approach to evaluate the presence of nationality discrimination in the English professional soccer league by estimating the effect of team nationality composition on attendance. He found that, by having more South American players, owners might benefit with increased attendance.

Tainsky and Winfree (2010) examined the presence of MLB fan discrimination relating to nationality using team's average attendance from the 1985 to 2005 season. They found that the net effect of the number of foreign players on a team increased demand, but the functional form is quite quadratic along with the interaction terms. Thus, the overall result showed that foreign players had a negative effect on demand and remained negative for almost half of the era, but turns positive in 1992 season such that when the effect peaked, one additional international player enabled teams to increase their annual revenue by $595,632.

CHAPTER THREE

METHODOLOGY & DATA

3. 1 Definition of Player

3.1.1 Star Players

In previous studies about superstars, a point of controversy concerned the notion that star players attracted fans by their superior talent and exceptional performance on the pitch (Rosen, 1981) or by their remarkable popularity (Adler, 1985). The results, therefore, are dependent on how superstar status is defined. In his research on the NBA, Jane (2014) defined a star player as “a player who makes top performances or who gets a top salary in the league” as a proxy of the exceptional performance, and “a player who is an All-Star player and the total votes received by the star player” as a proxy of the remarkable popularity. With five different variables of defining star players (e.g., top-30 performance and salary players, top-12 and top-25 All-Star players, and All-Star players’ total votes), he suggested that multiple variables of a star player made the analysis more complete.

However, it is doubtful whether the salary information of players have to be a performance indicator. According to Scully (1974), in the competitive labor market, the player’s wage reflects the player’s marginal revenue product. In this regard, salary information can be an indirect indicator measuring player’s performance on the pitch. In this study, however, star players are identified by three criteria—their base salary information, their performance, and their popularity. The detailed information about the variables related to these concepts are explained later in this chapter.

3.1.2 International Players

Similar to Tainsky and Winfree's (2010) definition, international players are defined by their country-of-origin. Then players are categorized into the confederation under the FIFA structure based on their nationality. There are six confederations recognized by FIFA—Asian Football Confederation (AFC), Confederation of African Football (CAF), Confederation of North, Central American and Caribbean Association Football (CONCACAF), Confederación Sudamericana de Fútbol (CONMEBOL), Oceania Football Confederation (OFC), and Union of European Football Associations (UEFA). In this case, the Canadian players are regarded as domestic players since MLS has integrated three Canadian clubs (Toronto FC, Vancouver Whitecaps, and Montreal Impact) into the league. Additionally, in terms of the confederation, the United States and Canada belong to CONCACAF but they are separated and regarded as a control group to see the individual effect by confederation on match attendance.

3.2 Model

3.2.1 General Demand Model

Borland and Macdonald (2003) introduced the concept that the fundamental demand for sports are determined by five main factors—consumer preferences, economic factors, quality of viewing, characteristics of the sporting contest, and supply capacity. The literature on attendance in professional sports has normally wrapped up these factors into the three following: game characteristics (GC), team characteristics/ performance (TC), and market characteristics

(MC). Thus, the basic equation for match attendance demand (*Attendance*) in the MLS is as follows:

$$Attendance = f(GC, TC, MC) \tag{1}$$

The quality of players as it relates to star and international players belongs to team characteristics/ performance. The dependent variable for this study is *Attendance*, representing a level game-day attendance between home and away team. In this study, two additional units of measurement are utilized because there are a potential issues using game-day attendance to estimate the effect of star and international players. As in sport industry cases, MLS attendance is constrained by the stadium capacity and some of MLS franchises do not play their home games in a soccer-specific stadium. The sports demand literature in professional sports also shows that the results can be dependent on which type of unit of measurement was being utilized. Therefore, a log-transformed match attendance (*LnATT*) and the ratio of the actual match attendance to stadium capacity (*ATTper*) are added to see whether there is any difference among these three units of measurement and which measurement is appropriate in MLS, empirically.

There is probably an additional issue to be considered while using the ratio of attendance to stadium capacity. Since some MLS clubs use a non-soccer-specific stadium but a multiplex stadium, the actual stadium capacity might be different from the official capacity. In other words, the MLS limits to some extent the maximum capacity. The official maximum capacity indicates this amount according to the MLS information. However, MLS makes all seats available when, for example, the game is played on national holidays and this makes the value of the capacity ratio above one. It is thus necessary to use a censored-regression technique in this case. Therefore, the capacity ratio should be censored when we conduct the regression if it is beyond one; this is known as the Tobit Model (Tobin, 1958). For example, RFK stadium, the home stadium of DC United in the 2007 season, the maximum capacity was officially 20,000 but it was fully opened for a game against LA Galaxy and the actual attendance was 46,686. A detailed explanation of how to implement the Tobit model is provided in the methodology section.

3.2.2 Variables of Interest

The quality of players (*Players*)—the main variables of interest—includes variables related to star and international players. The impacts of all variables related to star and international players are expected to be positive on match attendance. Star players are measured by three different proxies: their base salary information, their performance, and their popularity. A star player by the base salary information is defined as "a player who gets a top-10 (*Top10Sal*) and top-30 (*Top30Sal*) base salary at the beginning of each season." Salary information of players is available at the player's union website (http://www.mlsplayers.org). The MLS awards players at the end of the season based on the statistics and a star player on performance is defined as "a player who was awarded by the league in the previous season (*Awards*)." The league awards used are MLS Golden Boot, Goalkeeper of the Year, Defender of the Year, MVP, Comeback Player of the Year, Newcomer of the Year, Rookie of the Year, and Best XI Players. Finally, a star player is defined as "a player who was selected for the All-Star Game in the previous season (*AllStars*)" to represent national popularity. Based on the definitions of star player, this study measures the number of players for the home and away team who were on the roster for the game.

International player (*Inter*) is defined by country-of-origin and measured by a number of players in the starting line-ups and substitutes. Then all those players are grouped into six different confederations under the FIFA structure (i.e., *Africa*, *Asia*, *Europe*, *Central*, *South*, and *Oceania*) to see the individual impact on match attendance compared to the North Americans (including the Canadians). Similar to measuring star players, this measures the number of international players for the home and away team who were on the roster for a certain game.

For each of the indicators of star and international players, this first measures the sum of the number of such players regardless of the home and away team. Then it considers the home and away team separately to see whether there is a difference in terms of match attendance and superstar externality. During the regular season, MLS teams play a balanced schedule, which means each team plays one home and one away game with each team. From the fans' point of view, there is only one chance per season to watch an away team's superstar play at their home stadium. Thus, match attendance due to players for the away team is expected to increase. This is related to the concept of superstar externality. Jewell (2015) assumed that if the increase in attendance is seen mostly at away games, then superstar externality is present. Therefore, this study first takes a look at the whole picture of the player's effect on match attendance, then moves on to the separated effect by the home and away teams' players to see whether there is also externality in the MLS case.

3.2.3 Control Variables

From the concept of game characteristics, the quality of a team is measured by the total points earned by the home and away team before they play each other. As in all soccer leagues, MLS gives three points for a win, one point for a draw, and zero for a defeat. *PointsBH* and *PointsBA* represent the total points earned by the home and away team before the game. Measuring the points earned is one way of investigating competitive balance in MLS. The impact of *PointsBH* is expected to be positive and *PointsBA* negative. The literature on competitive balance indicates that game-day attendance is influenced by the relative strengths between the home and away teams (Forrest & Simmons, 2002). In most industries, for example, a firm's welfare is improved when competition is eliminated. In sports, however, the elimination of competition effectively eliminates the industry. Furthermore, other firms must not only continue to exist but also actually do better when their competitors are of relatively equal strength (Berri & Schmidt, 2006). Empirically, there have been different dimensions of competitiveness and for one of those, the closeness in quality between two teams competing against each other is expected to boost attendance. Jewell (2015) used the variable *Match Certainty*, the absolute value of the difference between the points-per-game of the home and away team prior to the game. The current study also uses *Pointsdiff*, computed as the absolute value of the difference between the total points earned before the game by the home and by the away team. It is expected to be negative if the closeness of match matters.

Opening is a dummy variable equal to one if the game is the opening game for the home team each season and it is expected to be positive. Match attendance is probably higher for opening game than the other games during the season. *Weekend* and *Holidays* are dummies equal to one if the game is held on a weekend or a national holiday; these are expected to be positive. Many of MLS regular season games are played during the week, unlike the European professional soccer leagues. Additionally, spectating sporting games has become an entertainment activity; thus MLS games on weekend or holidays are expected to have a higher attendance than games on other days. *Temp* and *Precip* are the mean temperature in Fahrenheit and the mean precipitation in inches of the nearest Metropolitan Statistical Area (MSA) from the MLS franchise location. *Temp* and *Precip* are expected to be negative.

To find the ambient temperature for watching the game, this study adds the variable *Tempwarm*, which was generated by the product of *Temp* and *DVwarm*. *DVwarm* is a dummy equal to one if the mean temperature is a certain degree Fahrenheit or higher. Using the variable, it is expected to see whether the attendance changes when the mean temperature of the day is above or below a certain degree Fahrenheit. As a pre-test using *Attendance* and *Top10Sal*, this study found evidence that 71 degrees in Fahrenheit is a candidate for people to watch the game at the stadium. Table 3.1 shows the pre-test results. The impact of *Tempwarm* is expected to be negative.

With respect to variables for the team characteristics/ performance, *StadiumAge* and *ClubAge* are the indicator variables, referring to the age of the stadium and that of the home team. Tainsky and Winfree (2010) considered the age of the stadium for capturing the novelty effect and the length of time the franchise has been in its current city to capture an increased fan base when a team has longevity in one location. Thus, the impact of both *StadiumAge* and *ClubAge* are expected to be positive. *Playoffs* and *Champ* are dummies equal to one if either the home team (*PlayoffsH* and *ChampH*) or away team (*PlayoffsA* and *ChampA*) qualified for the playoffs or won the championship the previous season. These all are expected to be positive.

The variables for the market characteristics to control for city-specific factors that affect match attendance are often measured by population and average income level where the MLS franchise is located. *Population* and *Income* represent the population and the per-capita personal income of the closest MSA where the home team city is located[3]. The U.S. Bureau of Economic Analysis (BEA) reports market-related information quarterly but the MLS regular season kicks off in the middle of March or in early April. Since the information of the first quarter is not available at the time the season begins, this study utilizes a one-quarter lagged information of both population and per-capita personal income. The effects of both population and per-capita income are expected to be positive.

3.3 Methodology

I examine three specifications of game-day attendance and variables for the game, team and market characteristics previously discussed, Equation (2) below is the data-specific equation for estimated demand for MLS using the Ordinary Least Squares (OLS) regression.

$$
\begin{aligned}
Attendance = {} & \beta_0 + \beta_1 Players + \beta_2 PointsBH + \beta_3 PointsBA + \beta_4 Opening + \beta_5 Weekend \\
& + \beta_6 Holidays + \beta_7 Temp + \beta_8 Tempwarm + \beta_9 Precip + \beta_{10} StadiumAGE \\
& + \beta_{11} ClubAGE + \beta_{12} PlayoffsH + \beta_{13} PlayoffsA + \beta_{14} ChampH \\
& + \beta_{15} ChampA + \beta_{16} Population + \beta_{17} Income + \varepsilon
\end{aligned}
\tag{2}
$$

Players include all indicators related to star and international player explained above. All βs are the parameters to be estimated and ε is the error term of the regression. The baseline regression includes an aggregate number of players regardless of considering the home and away

[3] Population and per-capita personal income information are available in the U.S. Bureau of Economic Analysis (BEA) website, retrieved from http://www.bea.gov.

team under the specification of a level match attendance as a dependent variable for each star and international player analysis case.

As briefly discussed above, in sport demand studies, attendance data are constrained by the capacity of the stadium. Thus, to account for the constraints, it may be necessary to use the censored-regression technique. Since this study uses the ratio of the actual match attendance to the stadium capacity as one of the specifications for the dependent variable, the values of observations should be less than or equal to one. The observations having a value larger than one are censored when conducting the regression approach, and this is known as the Tobit Model, first proposed in 1958 by James Tobin. Equation (2), for the case of using the ratio of attendance to the stadium capacity (*ATTper*), is extended by Equation (3)

$$ATTper^* = \alpha + \beta Players + X'\gamma + \varepsilon \quad (3)$$

where $ATTper^*$ is a latent (i.e., unobservable) variable, α is the constant, X is the matric of control variables, and ε is the error term. This variable linearly depends on *Players* by β which determines the relationship between *Players* and $ATTper^*$. The error term (ε) is assumed to be normally distributed. The observable variable (*ATTper*) is defined as being equal to the latent variable ($ATTper^*$) whenever the latent variable is smaller than one or being equal to one, otherwise. Thus, the observed *ATTper* is definded as Equation (4),

$$ATTper = \begin{cases} ATTper^* & if\ ATTper^* < 1 \\ 1 & if\ ATTper^* \geq 1 \end{cases} \quad (4)$$

Thus, combining Equations (3) and (4) gives us:

$$ATTper = \begin{cases} \alpha + \beta Players + X'\gamma + \varepsilon & if\ ATTper^* < 1 \\ 1 & if\ ATTper^* \geq 1 \end{cases} \quad (5)$$

From the 2004 to the 2014 season, according to the dataset, out of 2,201 MLS games, sellouts occurred 414 times, accounting for about 19 percent. The upper limit of the attendance ratio is set to be equal to one.

3.4 Data Description

This study chose the MLS match attendance data of the regular seasons from 2004 to 2014, collected from the official MLS website (http://www.mlssoccer.com) and other sport reference websites (e.g., http://www.soccerstats.us). Measuring game-day attendance data is one of the easiest and the most direct proxies for measuring demand for the MLS because the MLS and other reference websites offer available attendance information for every single game. The gate receipts as they relate to match attendance are the traditional but still one of the largest single sources of revenue, and this supports the economic relationship between attendance and a team's profitability (Blair, 2011; Humphreys, 2015).

The data contains information on 19 MLS teams at most, and it covers all 2,529 regular season games for that period. MLS consisted of 10 teams in the 2004 season and by 2012 had expanded to 19 teams. There were minimally 150 games with 10 teams playing 30 rounds in 2004 season and maximally 323 games with 19 teams playing 34 rounds since the 2012 season. Table 3.2 shows a snapshot information of each season since 2004.

Since the MSA information (i.e., population and per-capita personal income) is limited regarding Canada, three Canadian clubs—Toronto FC, Vancouver Whitecaps, and Montreal

Impact—were omitted from the data. The total number of observations for this study were 2,201 games and the descriptive statistics including all variables are listed in Table 3.3.

CHAPTER FOUR

EMPIRICAL RESULTS AND DISCUSSION

4.1 Star Effect on Demand

4.1.1 Aggregate Effect[4]

As a dependent variable, match attendance has three specifications—the level attendance, the log-transformed, and the ratio of actual attendance to the capacity of stadium. Thus, in each section of analysis, the regression result using the level game-day attendance will be the baseline regression. The four main variables of interest (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) and the control variables with respect to the game, team, and market characteristics are the same across all the regressions. The regression results can be found in Tables 4.1 - 4.3.

The study utilized the censored-regression technique (i.e., Tobit Model) in the case of stadium capacity ratio (*ATTper*), as the official capacity of each stadium varies; that is, the right-censored point for the audience is a fixed number. Thus, the upper limit of the attendance ratio is set to be equal to one. In the 10 seasons from 2004 to 2014, the dataset shows that sellouts occurred 414 times out of 2,201 games, accounting for approximately 19 percent. Regarding how the regression coefficients are interpreted, there should be a change in percent (%) in the case of using a log-transformed dependent variable and the percentage point change in the stadium

[4] For the sensitivity tests, this study also have three different regression processes: 1. by excluding David Beckham, 2. by dividing Top10Sal into four categorical variables, and 3. by imposing a quadratic form of Top10Sal. The results are in Appendices (A) – (C).

capacity ratio case after multiplying by a hundred, respectively.

Among the variables of interest, only salary information (*Top10Sal* and *Top30Sal*) was statistically significant across all specifications of the attendance, and the magnitude is fairly large. The marginal effect of a top-10 paid player on game-day attendance was about 2,368 people. This is a huge change in attendance, given the average attendance is 16,986; holding all else constant, one top-10 paid player brought about 13.94% of the expected attendance increase. On the other hand, under the log-transformed attendance and the stadium capacity ratio, the changes in the expected attendance are 11.8 percent and 3.71 percentage points. Taking the level attendance result, one additional top-10 paid player generated roughly \$109,449 ($= \$46.22 \times 2{,}368$) more ticket revenue per game, given the average ticket price of MLS in 2015 referred from the GoEuro Soccer Price Index[5].

Assuming the empirical fact that a player's wage reflects the marginal revenue product (Scully, 1974), the result seems to be reasonable. After all, top-10 paid players are evaluated to perform better than top-30 players by the league and they are expected, when they make an appearance, to draw more fans to the stadium. Ultimately they generate more revenue for the league. However, star performance (*Awards*) and popularity (*AllStars*) are still insignificant and negatively affect game-day attendance. Table 4.4 shows the marginal ticket revenue simply calculated from the dataset based on the regression results that top-10 paid players generate by year. Top-10 paid players generate much higher revenue than that of their average base salaries.

[5] The average ticket price of soccer leagues in 2015 available at GoEuro Soccer Price Index, retrieved from http://www.goeuro.com/soccer-price-index.

In general, if the differences of coefficients across all specifications had close values, it would be unnecessary to check the distribution of dependent variable. Tables 4.1 – 4.3 show that the difference between all specifications is not huge but it might be necessary to select the right functional form of attendance. For a robust analysis, therefore, the next step is to check the normality assumption of dependent variable and for this study to find the better form of game-day attendance.

In Statistics, a QQ plot is often used to compare the shape of distribution of sample observations to theoretical normal distribution. Providing a graphical view, the solid line indicates a perfectly normal distribution while the dotted line indicates the distribution of sample observations. Since there is no perfectly normal distribution case using the sample, it may be concluded that the sample is normally distributed as the dotted line follows closely the solid line. Figures 4.1 – 4.3 show the QQ plots for each specification of game-day attendance. According to these figures, it is more reasonable to use a log-transformed attendance because when using a level attendance and the stadium capacity ratio outliers appear. This suggests that a real stadium capacity shifts according to the demand and corresponds to the fact that the maximum capacity of certain stadiums (being controlled by MLS) is flexible.

In terms of star effect on attendance, only piece of salary information (*Top10Sal* and *Top30Sal*) meets the expectation of a positive effect on attendance. Top10-paid players have a strong positive impact on the attendance change and top-30 paid players also have a positive impact. However, when it comes to other measurements of star players (*Top30Sal*, *Awards*, and *AllStars*), an inconsistency arises in terms of statistical significance. The direction of *Awards* across all specifications of attendance is negative. These results are completely opposite to the expectation, suggesting that in this study the indexes for estimating both performance and popularity of players are flawed. These results call for further explanation.

These results may be explained in two ways. One is that the criteria of measuring player's performance and popularity, because of their subjectivity, is from the start inappropriate. Thus, it is necessary to find more precise measures for performance and popularity when dealing with MLS. Previous studies offered several alternatives. In soccer, for example, Brandes et al. (2008) imposed the sum of weighted goals and assists by position for performance indicator and the media attention for popularity indicator. How frequently German's top-20 newspapers and magazines printed a player's name served as a proxy of the player's popularity in a study of Bundesliga, Germany's highest professional soccer league. However, it is a very subjective matter to find the better indexes because soccer is a highly interactive game based on the combination of complementary player skills (Carmichael, Thomas, & Ward, 2001). Hence, we do not have depth regarding player performance indicators for more individualistic North American team sports such as baseball and basketball (Lucifora & Simmons, 2003).

A second way to explain these results might be to show the direction of the fan preference for players. That is, it matters whether the direction of expectation by the fans is forward or backward. In other words, MLS fans, prior to the season, hold expectations for star players "toward" by scrutinizing the salary information whereas the players' information based on the performance and popularity in this study reflected fans' expectation from "past" information because those indicators have the lagged experience. Thus, the benefit of this study is to find evidence of whether the direction of fans' preference for the marquee players is forward- or backward-looking. Having negative regression coefficients, therefore, the answer to this question is that the market picks the salary information up rather than the past experiences with respect to the expectations of star players in the current season.

For the control variables with respect to game characteristics, the majority of coefficients show the expected directions without considering the statistical significance and are fairly consistent across the specifications of game-day attendance. Having the greatest impact on attendance change was *Holidays* while *Precip* had the smallest. Putting the statistical significance aside, the only exception of direction against the expectation is *Temp*, as shown in Table 4.3, and it is positive and statistically significant. However, this study imposes *Tempwarm* because the mean temperature *per se* may be not enough. Thus, the direction change of *Temp* is negligible here. It seems to be more reasonable for *Tempwarm* to be interpreted as follows: A one-degree increase in Fahrenheit beyond 71 degree leads to 0.1 percentage point decrease in game-day attendance on average, holding all else constant.

Taking the results from the baseline regression, Table 4.1, one point earned by the home team before the game (*PointsBH*) increased the expected attendance by 169 people, accounting for a roughly 1% increase given the average attendance, whereas one point earned by the visiting team (*PointBA*) decreased the expected attendance by 69 people, holding all else constant. League standing is calculated by points earned and serves as one way of defining competitive balance—how closely two teams are in the standings to one another. Given this, the current study utilized the variable *Pointsdiff*, the absolute value of the difference between the total points earned before the game by the home and by the away teams. Throughout all regression results, the variable is positive and statistically insignificant against the expectation. This means that as the difference of quality between two teams increases so does match attendance. Thus, it is suggested that the closeness of match does not matter and there is no evidence in terms of competitive balance in the MLS case.

For the team characteristic variables, all coefficients show the expected direction and are fairly consistent across all specifications of attendance with the exception of the age of the home team (*ClubAge*). From Table 4.1, *PlayoffsH* has the greatest impact on attendance change while *ClubAge* has the smallest. But in Tables 4.2 and 4.3, *ChampH* is highest. As discussed, *ClubAge* is expected to capture an increased fan base when a team has longevity in one location but it decreases the expected match attendance by 599 as the home team age is increased by one year. As shown with previous studies, this point is not consistent. Tainsky and Winfree (2010) found a positive relationship between attendance and club age in the MLB whereas Jane (2014) found a negative direction in the NBA case. Thus, the direction of *ClubAge* is negligible at this point.

In regards to the market characteristics, only per-capita personal income by MSA has a positive impact on the change in attendance across all specifications. However, the marginal effect of *Population* is negative in Table 4.3 against the expectation and statistically significant. This implies that the average attendance decreases as the population by MSA increases. However, it is not obvious how to interpret this unusual and unexpected result.

4.1.2 Home and Away Effect

Tables 4.5 – 4.7 show the regression results under different specifications of match attendance to see the individual home and away team effect. All other control variables with respect to the game, team, and market characteristics are the same as the former aggregate regression analyses. As with the former one, Table 4.5 is a baseline regression to be compared with the other two regression results.

Among four different indicators of star players, neither home nor away team is simultaneously significant across all specifications of game-day attendance. Only *Top10Sal* for both home and away team is statistically significant under the level and the log-transformed attendance and Top30Sal is statistically significant under the log-transformed attendance. Taking *Top10Sal* in Table 4.5, a top-10 paid player on a home team is expected to increase attendance by 2,321 people while a top-10 player on the visiting team is expected to increase attendance by 2,409 people, holding all else constant. These are 12.2 percent and 11.4 percent increases (shown in Table 4.6) and this implies that the impact by star players from visiting teams – while positive – is greater than that by home team star players. In addition, there is the same issue of getting a negative impact of *Awards* and *AllStars* in the result. Therefore, it is impossible to compare the relative impacts on attendance by home and away teams using other indicators of star players except *Top10Sal*.

The purpose of dividing the aggregate effect into home and away team is to estimate whether there is evidence of superstar externality in the MLS. Previous studies on star players have found evidence that a superstar is expected to boost attendance more at away games rather than at home games (Berri & Schmidt, 2006; Hausman & Leonard, 1997; Jane, 2014; Jewell, 2015). However, there are two potential issues of analyzing the externality using the results in this study. To exactly analyze the superstar externality, the impact by the "same" player or group of players when they play at home must be compared to that impact when they play on the road. For example, Jewell (2015) considered three Designated Players (DPs), David Beckham, Cuauhtémoc Blanco, and Rafael Márquez, and found evidence of the externality by measuring the impact of each player on attendance when they play at home and away separately. Further, to investigate the precise externality of star players, for example, Berri and Schmidt (2006) utilized road attendance. However, the variables in this study merely indicate the number of players on the home and away teams, and the attendance recorded is for the home game. Therefore, to circumvent this problem and see whether superstar externality exists in the MLS, one more step is needed.

In order to compare two coefficients for home and away team, the first step is to assume that these two groups of players are not different in terms of doing a regression process by the results from the test of equality ($H_0: \beta_1 = \beta_2$). If we do not reject the null, then two different groups of players would be considered the same. Then by doing the jointly significance test ($H_0: \beta_1 = 0, \beta_2 = 0$) and if we reject the null, we can examine whether there is externality or not. The table below shows the criteria of determination, for example of using the coefficients for *Top10Sal*.

Externality	Coefficient	Test for Equality	Test for Joint Significance
No Externality	$Top10SalH > 0$ $Top10SalA \leq 0$	None	None
Positive Externality	$Top10SalH > 0$ $Top10SalA > 0$	None	Reject the Null
Strong Positive Externality	$Top10SalH > 0$ $Top10SalA > 0$	Do not Reject the Null	Reject the Null

Since only *Top10Sal* and *Top30Sal* have a positive coefficient, it is impossible at this point to check the externality using *Awards* and *AllStars*. Taking the level and the log-transformed attendance which result in a positive coefficient, Tables 4.8 and 4.9 show the results of testing equality and joint significance, respectively. From the test results, both top-10 and top-30 paid players have a strong positive externality under the level and log-transformed match attendance. Therefore, there is evidence that a superstar externality exists in terms of the salary information in the MLS.

The majority of the control variables associated with the game, team, and market characteristics show almost the same results as the former aggregate effect results across all specifications of attendance in terms of the statistical significance and the direction. There are also some changes in the direction of the regression coefficients (*Temp* and *Population*) but the possible explanation for getting these results is the same as that given above.

4.2 International Player Effect

4.2.1 Aggregate Effect

Considered customer discrimination in MLB, Tainsky and Winfree (2010) imposed a *Matching* variable, calculated by a simple aggregation of the product of the proportion of each team from a given country and the proportion of the corresponding MSA population on their model. The reason for imposing this variable on the model was to see whether the change in demand attributable to foreign-born players could be found in the fan population identifying with those countries. However, the change was not significant, suggesting that not only foreign-born fans tend to watch the game for their countrymen playing but also non-international fans want to watch those same players playing for their favored team as well. Therefore, the only interesting variable utilized in this study is the number of foreign players by nationality (*Inter*) to see the aggregate effect of international players on demand.

Table 4.10 shows the results of the aggregate international player effect on game-day attendance across all specifications of attendance. As with the analysis of star effect, the regression using the level attendance is the baseline regression; it is represented in the second column of Table 4.10. The other two columns represent the regression results under a log-transformed attendance and the ratio of actual attendance to stadium capacity, respectively. All of the control variables with respect to the game, team, and market characteristics are the same across all specifications of attendance.

It is obvious that foreign-born players positively influence the change in match attendance. The direction of *Inter* in each column is positive and statistically significant. As one additional foreign-born player plays on the pitch, the average attendance is expected to increase by 224 people, holding all else constant. This increase corresponds to 1.22 percent and 1.47 percentage points increase under a log-transformed attendance and the stadium capacity ratio. Given the average game-day attendance, the difference in magnitude of the change across all specifications is not significant. The implication is that since the regression results about international player effect are fairly consistent, MLS fans seem to prefer to watch foreign players playing on the pitch.

For the control variables of the game characteristics, all variables were statistically significant regardless of the significance level and show the expected direction except *Temp* and *Tempwarm*, as we see in the second column of Table 4.10. However, as noted above, the problem of *Temp* is negligible and also under a log-transformed attendance and the stadium capacity ratio, the coefficient of *Tempwarm* is statistically significant. *Holidays* has the biggest impact while the *Precip* has the smallest—the same as the results of the analyses of star players. Therefore, it is concluded that the regression results with respect to the control variables of this study are fairly consistent and robust.

With respect to the variables of team characteristics, all regression coefficients are statistically significant across all specifications of attendance except for *PlayoffsA* without considering its significance level. Further, the direction of coefficients is exactly the same as the expectation. *ChampA* has the biggest impact on match attendance and it accounts for approximately 1,844 people; it is expected to, as the incoming guest team were in the playoffs the previous season. *ClubAge* has the smallest effect on attendance but its direction is still controversial. It shows that a one-year increase in the age of the home team leads to decrease in game-day attendance by 28 people on average, holding all else constant.

Regarding the market characteristics, *Population* is statistically significant and consistent across all specifications but still problematic because of its direction in the case of using *ATTper*. Per-capita personal income by the MSA positively affect the game-day attendance and is statistically significant and consistent across different specifications of match attendance.

4.2.2 Home and Away Effect

As with star players, the aggregate number of international players is divided into home and away teams. The same potential problem of comparing the magnitude of the coefficient may occur as in superstar externality. Table 4.11 shows the regression result of all specifications of game-day attendance and the second column using the level attendance as a dependent variable is the baseline regression.

InterH is statistically significant and consistent across all specifications of match attendance. Specifically, an additional international player in the home team increases the expected attendance by 416 people, holding all other variables constant. This is 2.18 percent and

2.14 percentage points under the other two specifications of attendance, respectively. However, *InterA* is statistically insignificant except for the result under ATTper as a dependent variable. The marginal effect of *InterA* is 0.83 percentage points.

With respect to the control variables for game, team, and market characteristics, all the coefficients are statistically significant and consistent across all specifications with the exception of *PointsBA*, *Temp*, and *Population*. The direction of *Temp* turns out to be positive under a log-transformed attendance and the stadium capacity ratio. Among all control variables, *Holidays* has the greatest impact and *Precip* has the smallest. In other words, the games played on the national holidays are expected to increase attendance by 6,155 people (37.5 percent and 33.1 percentage points), holding all else constant.

4.2.3 Effect by Confederation

Table 4.12 shows the results of the international player effect by the confederation under the FIFA structure across all specifications of attendance. The variables of interest are *Africa*, *Asia*, *Europe*, *Central*, *South*, and *Oceania*. Thus, domestic players, both the American and Canadian players, make up the control group for comparing the effect of other groups of players. The result in the second column is the baseline regression. All coefficients for the variables of interest show the expected direction except for *Oceania*. Note that all coefficients under *ATTper* are statistically significant. Without considering its significance, *Asia* has the greatest impact, accounting for an attendance increase of 1,511 people as one additional Asian player plays on the pitch compared to the effect of an additional domestic player, holding all else constant. It is 7.29 percent and 5 percentage points under LnATT and ATTper, respectively. Across all specifications, only *Africa* and

Asia are consistent in terms of their statistical significance and direction.

In regards to all control variables for game, team, and market characteristics, the majority of coefficients are statistically significant and have the expected direction. Among all control variables, *Holidays* has the greatest effect while *Precip* has the smallest. Games played on national holidays are expected to attract 5,827 more people to the stadium, on average, holding the other variables constant. This is roughly 34.3 percent ($= \frac{5,827}{16,986} \times 100\%$), given the average attendance of the dataset. This value is very close to the coefficients using *LnATT*.

In this study, the portion of international player effect is smaller than the star player effect. The purpose of this study on international player effect is to examine how MLS fans react in terms of game-day attendance to the presence of foreign-born players playing on the field. Its effect on change in attendance is smaller than that of star players but is still positive and statistically significant. Additionally, the results from analyzing the individual effect by host and guest team, and by confederation under the FIFA structure suggest there might be potential for additional research, especially in MLS case. For example, it is also good to specify the salary information, performance, and popularity indicators on international players and see those individual effects on attendance change. In this study, however, it was limited to collect all salary information of those players given the huge number of international players.

Further, when the evidence from this study is all taken together, a potential topic in terms of playing quality being one of the determinants of demand for professional sports might be the foreign-born 'star' player effect on match attendance. Since the 2007 season when the MLS first accepted David Beckham into the league by the Designated Player (DP) rule, the majority of top-

10 paid players have been foreign-born players. This can be seen in Table 4.13, which shows the names of top-10 paid players and the number of DPs and international players. Therefore, future studies may explore this topic and explain how the change in consumer preference occurs.

Lastly, some of the previous studies on customer discrimination imposed a certain variable related to the concept of how similar is the proportion of players in each team to the proportion of the population in the city where each team is located. This was motivated by the hypothesis of the presence of nationality discrimination in sports (Pedace, 2008; Tainsky & Winfree, 2010). In their customer discrimination study on MLB, Tainsky and Winfree (2010) imposed the *Matching* variable. This was an aggregate of the product of the proportion of each team from a given country and the proportion of the corresponding MSA population, although the authors found it not to be significant. However, none of the previous research on customer discrimination in MLS has used this variable. Thus, for further research, it would be interesting to know what presence this has in MLS. At this moment, however, the contribution of this study is to investigate merely whether there is a positive impact on fan preference (or customer discrimination) regarding foreign players and the regions from which they come.

CHAPTER FIVE

CONCLUSION

With its relatively short history and the great popularity of other major leagues, professional soccer in the U.S. has historically struggled for mainstream attention. However, in lots of small, almost imperceptible ways, things have started to get better financially and operationally. Such success may in part be attributed to the league having its own unique structure. Most of all, the success is because of the improvement in the quality of playing, one of the determinants of demand for sports. Since the 2007 season, the Designated Player rule in the MLS has allowed the league to better compete in the international soccer markets. Though it is dependent on the definition of superstar status, a lot of the superstar literature has found evidence that a star player influences the demand for sport, especially in terms of match attendance (see Berri & Schmidt, 2006; Berri et al., 2004; Brandes et al., 2008; Franck & Nüesch, 2012; Hausman & Leonard, 1997; Jane, 2014; Jewell, 2015; Lawson et al., 2008; LeFeuvre et al., 2013; Mullin & Dunn, 2002; Rivers & DeSchriver, 2002). Previous literature about customer discrimination found evidence that fans respond to the racial composition of the team in terms of the change in match attendance (see Burdekin et al., 2005; Burdekin & Idson, 1991; Hoang and Rascher, 1999). Therefore, the purpose of this study was to continue to explore a relationship between star and international players on match attendance in the MLS from the 2004 to 2014 seasons.

In terms of star effect, only stars as defined by salary information (*Top10Sal* and *Top30Sal*) exhibited a positive relationship on match attendance (regardless of statistical significance). This study found evidence that only a top-10 paid player yield a statistically significant increase in attendance. Numerically, one additional top-10 paid player generated roughly \$109,449 ($= \$46.22 \times 2{,}368$) more ticket revenue per game, given the average ticket price of \$46.22 in 2015. However, stars as defined by their performance (*Awards*) or by their popularity (*AllStars*) had a negative effect on match attendance. Such a finding suggests that the method for measuring those is either inappropriate, or MLS fans set their expectations of players in a forward direction rather than a backward direction. Franck and Nüesch (2012) indicated that measuring the specific contribution to a soccer game and the exact talent of a star player is difficult because a soccer match is a team product. Thus, a future study is needed to find more precise measurements for player's performance and popularity in soccer. However, the implication of these results favors the enactment of the Designated Player rule, though critics of the rule argue that it aggravates income disparity among players and hampers domestic youth development.

Further, among three different specifications of match attendance (level attendance, a log-transformed attendance, and the ratio of actual attendance to the stadium capacity), this study found that it is more reasonable to use a log-transformed match attendance when analyzing the player effect in the MLS. Given this result, this study found evidence that star players (as defined by their salaries) exert a strong positive externality in the MLS. Jewell (2015) found evidence that two designated players, David Beckham and Cuauhtémoc Blanco, had externality effects during their careers in the MLS. Thus, the result of this study, though it is limited to star players defined by salary information, might imply the possibility of generalization that superstar externality indeed exists even by analyzing the whole group of star players not a certain player or group of players. However, the method of examining superstar externality in this study was not appropriate. Hence, a future study needs to find evidence of the exact externality by using road attendance data.

Regarding the international player effect on match attendance, it is obvious that foreign-born players positively influence changes in match attendance regardless of the specifications of match attendance. Further, from the results of individual effect by confederation under the FIFA structure, only African and Asian players are statistically significant. For example, an additional Asian player leads to increase in match attendance by 1,511 more than an additional domestic player, holding all else constant. Further, combining the evidence of these results with the result that only salary information is significant when it comes to star effect, a future study is needed to find the sole effect of the foreign-born star player in the MLS, since the majority of top-10 paid players are foreign-born DPs, as shown in Table 4.13. In addition, since this study does not impose the "matching" variable related to the product of racial composition between team and population of the market area covered by the team, a future study is needed to find the exact evidence of customer discrimination in the MLS.

FIGURES AND TABLES

Table 1.1

Average Attendance per Season

Season	Total Attendance	Games	Average Attendance	Change (last year)	Change (1996)
1996	2,785,001	160	17,406		
1997	2,339,019	160	14,619	-16.01	-16.01
1998	2,747,897	192	14,312	-2.10	-17.78
1999	2,742,102	192	14,282	-0.21	-17.95
2000	2,641,085	192	13,756	-3.68	-20.97
2001	2,363,859	158	14,961	8.76	-14.05
2002	2,215,019	140	15,822	5.75	-9.10
2003	2,234,747	150	14,898	-5.84	-14.41
2004	2,333,797	150	15,559	4.44	-10.61
2005	2,900,716	192	15,108	-2.90	-13.20
2006	2,976,787	192	15,504	2.62	-10.93
2007	2,976,423	165	16,642	8.17	-3.65
2008	3,456,600	210	16,460	-1.85	-5.43
2009	3,608,325	225	16,037	-2.57	-7.87
2010	4,002,000	240	16,675	3.98	-4.20
2011	5,468,951	306	17,872	7.18	2.68
2012	6,074,729	323	18,807	5.23	8.05
2013	6,010,384	323	18,608	-1.06	6.91
2014	6,184,804	323	19,148	2.90	10.01
2015	7,326,899	340	21,574	12.67	23.95

Source: Attendance and game data were obtained from the season recap on MLS's official website, [http://www.mlssoccer.com].

Note: The last two columns stand for the percentage change compared to the previous season and the inaugural season. Attendance data include all Canadian clubs (Toronto FC, Vancouver Whitecaps, and Montreal Impact) from the 2007 season (see Table 3.2).

Table 3.1

Pre-Test Results for the Ambient Temperature

	51°F	61°F	71°F	81°F
R-Squared	0.2314	0.2314	0.2322	0.2314
Adj R-Squared	0.2215	0.2215	0.2223	0.2215
Coefficient	4.753236	-0.4420571	-10.25932	-1.274949

Note: Using ordinary least squares, the analysis utilized as a dependent variable level match attendance (*Attendance*) and as an independent variable the number of top-10 paid players (*Top10Sal*). The coefficient stands for the regression coefficient for *Tempwarm*, the product of mean temperature and *DVwarm*, which equals to one if the mean temperature is a certain temperature (51°F, 61°F, 71°F, and 81°F) or higher.

Table 3.2

League Information

Year	Teams	Canadian Clubs	Total Games	Total Rounds
2004	10 teams	None	150 games	30 rounds
2005	12 teams	None	192 games	32 rounds
2006	12 teams	None	192 games	32 rounds
2007	13 teams	Toronto FC	165 games	30 rounds
2008	14 teams	Toronto FC	180 games	30 rounds
2009	15 teams	Toronto FC	195 games	30 rounds
2010	16 teams	Toronto FC	210 games	30 rounds
2011	18 teams	Toronto FC, Vancouver Whitecaps	240 games	34 rounds
2012	19 teams	Toronto FC, Vancouver Whitecaps, Montreal Impact	226 games	34 rounds
2013	19 teams	Toronto FC, Vancouver Whitecaps, Montreal Impact	226 games	34 rounds
2014	19 teams	Toronto FC, Vancouver Whitecaps, Montreal Impact	225 games	34 rounds

Source: Same as Table 1.1

Note: A snapshot of information from each season since the 2004 season. Total number of games per season excludes games played by Canadian clubs wherever they played both at home and on the road.

Table 3.3

Descriptive Statistics of the Data

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable						
Attendance	Game-Day Attendance	2,201	16,986.22	8,180.351	3,702	92,650
LnATT	log(Attendance)	2,201	9.650986	0.4108886	8.216628	11.43658
ATTper	Ratio of Attendance to Stadium Capacity	2,201	0.7020318	0.3124626	0	5.850071
Star Players						
By Salary						
Top10Sal	Number of Top 10 Base Salary Players	2,201	0.4366197	0.7708934	0	4
Top10SalH	Number of Top 10 Base Salary Players for Host Team	2,201	0.2126306	0.5136717	0	3
Top10SalA	Number of Top 10 Base Salary Players for Visiting Team	2,201	0.2239891	0.5293965	0	3
Top30Sal	Number of Top 30 Base Salary Players	2,201	1.575647	1.365093	0	8
Top30SalH	Number of Top 30 Base Salary Players for Host Team	2,201	0.7969105	0.8718369	0	5
Top30SalA	Number of Top 30 Base Salary Players for Visiting Team	2,201	0.7787369	0.9018277	0	5
By Performance						
Awards	Number of Players Awarded in Previous Season	2,201	0.812358	0.9461654	0	5
AwardsH	Number of Players for Host Team Awarded in Previous Season	2,201	0.408905	0.6835687	0	4
AwardsA	Number of Players for Visiting Team Awarded in Previous Season	2,201	0.403453	0.6761299	0	4
By Popularity						
AllStars	Number of All-Star Players voted in Previous Season	2,201	1.728305	1.515305	0	9
AllStarsH	Number of All-Star Players for Host Team voted in Previous Season	2,201	0.8736938	1.049434	0	6
AllStarsA	Number of All-Star Players for Visiting Team voted in Previous Season	2,201	0.8546115	1.055177	0	6
International Players						
By Nationality						
Inter	Number of Foreign Players by Nationality	2,201	9.813267	3.085174	1	20
InterH	Number of Foreign Players for Host Team by Nationality	2,201	4.936847	2.096775	0	11
InterA	Number of Foreign Players for Visiting Team by Nationality	2,201	4.87642	2.076096	0	11
By Confederation						
Africa	Number of Foreign Players from Africa	2,201	1.333485	1.321711	0	8
Asia	Number of Foreign Players from Asia	2,201	.2848705	.5267336	0	3
Europe	Number of Foreign Players from Europe	2,201	1.954112	1.608269	0	11
Central	Number of Foreign Players from Central America and Caribbean Islands	2,201	3.249886	1.834835	0	12
South	Number of Foreign Players from South America	2,201	2.880963	2.009841	0	11
Oceania	Number of Foreign Players from Oceania	2,201	.10995	.3576388	0	3

Game Characteristics						
PointsBH	Total Points Earned by Host Team before the Game	2,201	21.23944	14.29998	0	64
PointsBA	Total Points Earned by Visiting Team before the Game	2,201	21.53294	14.24149	0	67
Pointsdiff	Absolute Value of Difference between PointsBH and PointsBA	2,201	6.445252	6.08641	0	41
Opening	Dummy of Opening Game for Host Team (YES = 1, Otherwise = 0)	2,201	0.0622444	0.2416539	0	1
Weekend	Dummy of Weekend Game(Weekend = 1, Otherwise = 0)	2,201	0.7941845	0.4043882	0	1
Holidays	Dummy of National Holidays Game (Holidays = 1, Otherwise = 0)	2,201	0.0168105	0.1285903	0	1
Temp	Mean Temperature of the Day When Game Played	2,201	67.20082	11.37408	24	96
Tempwarm	Interaction Term between Temp and Dvwarm*	2,201	31.01545	38.32344	0	96
Precip	Precipitation of the Day When Game Played	2,201	0.0908042	0.3204479	0	6.18
Team Characteristics						
StadiumAge	Age of the Stadium	2,201	20.6129	24.14438	1	89
ClubAgeH	Age of the Host Team	2,201	12.2458	5.231549	1	21
PlayoffsH	Dummy of Playoffs for Host Team (YES = 1, Otherwise = 0)	2,201	0.59791	0.4904313	0	1
PlayoffsA	Dummy of Playoffs for Visiting Team (YES = 1, Otherwise = 0)	2,201	0.6001817	0.4899721	0	1
ChampH	Dummy of Champion for Host Team (YES = 1, Otherwise = 0)	2,201	0.0726942	0.2596929	0	1
ChampA	Dummy of Champion for Visiting Team (YES = 1, Otherwise = 0)	2,201	0.0726942	0.2596929	0	1
Market Characteristics						
Population	Population of Host City	2,201	6,404,627	5,199,075	982,034	19,900,000
Income	Per-Capita Personal Income in Host City	2,201	46,050.9	7,620.6	31,245	69,205

Source: Match attendance, awards, and All-Star players from MLS official website, [http://www.mlssoccer.com] and other sport reference websites, [http://www.soccerstats.us] and [http://www.espn.com] from the 2004 to 2014 season. Player's salary information from MLS Player's Union website, [http://www.mlsplayers.org]. Temperature and precipitation from [https://www.wunderground.com]. Population and per-capita personal income from the U.S. Bureau of Economic Analysis [http://www.bea.gov].

Note: All Canadian clubs were omitted from the data. **DVwarm* =1 if *Temp* >= 71°F

Table 4.1

Regression Results of Star Players (Dependent Var. Attendance)

Dependent Var.	Attendance	Attendance	Attendance	Attendance
Top10Sal	2367.7*** (233.6)			
Top30Sal		476.9*** (142.8)		
Awards			-59.10 (182.3)	
AllStars				89.57 (120.1)
PointsBH	168.9*** (19.11)	177.1*** (19.49)	177.8*** (19.54)	177.5*** (19.54)
PointsBA	-68.63*** (19.42)	-72.93*** (19.82)	-72.35*** (19.87)	-72.20*** (19.87)
Pointsdiff	18.60 (28.78)	18.60 (29.38)	17.73 (29.45)	18.45 (29.46)
Opening	2660.8*** (723.9)	2711.7*** (739.3)	2807.9*** (740.8)	2776.6*** (741.5)
Weekend	933.8* (393.3)	946.2* (401.8)	1007.2* (402.4)	997.1* (402.6)
Holidays	5700.6*** (1234.7)	5926.1*** (1260.2)	6003.9*** (1263.3)	6017.9*** (1263.1)
Temp	-19.34 (24.28)	-22.71 (24.79)	-21.24 (24.85)	-22.15 (24.88)
Tempwarm	-10.26 (6.786)	-11.38 (6.927)	-11.82 (6.945)	-11.45 (6.956)
Precip	-1408.5** (484.2)	-1408.9** (494.3)	-1437.5** (495.5)	-1438.8** (495.4)
StadiumAge	-35.45*** (7.268)	-29.08*** (7.391)	-28.78*** (7.456)	-29.42*** (7.425)
ClubAgeH	-599.2*** (34.89)	-571.2*** (35.51)	-571.8*** (35.70)	-571.6*** (35.63)
PlayoffsH	1418.7*** (342.6)	1445.5*** (349.7)	1487.1*** (355.5)	1426.2*** (355.0)
PlayoffsA	661.4* (332.6)	643.4 (339.5)	644.1 (343.4)	595.0 (343.3)
ChampH	722.4 (625.3)	1088.6 (639.1)	1340.5* (643.3)	1239.8 (644.4)
ChampA	711.0 (616.5)	1200.8 (630.6)	1534.2* (636.8)	1413.4* (635.6)
Population	0.0000155 (0.0000314)	0.0000589 (0.0000318)	0.0000536 (0.0000319)	0.0000548 (0.0000319)
Income	0.179*** (0.0280)	0.155*** (0.0285)	0.157*** (0.0286)	0.158*** (0.0286)
_cons	9330.6*** (1971.4)	11258.9*** (2024.0)	12599.6*** (1993.5)	12535.8*** (1991.1)
N	2201	2201	2201	2201
R-sq	0.232	0.200	0.196	0.196
adj. R-sq	0.222	0.190	0.186	0.186

Source: Same as Table 3.1

Note: Values in parentheses are the standard errors. Main independent variables (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) stand for the aggregate number of star players. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.2

Regression Results of Star Players (Dependent Var. LnATT)

Dependent Var.	LnATT	LnATT	LnATT	LnATT
Top10Sal	0.118*** (0.0114)			
Top30Sal		0.0302*** (0.00698)		
Awards			-0.0106 (0.00892)	
AllStars				0.00487 (0.00588)
PointsBH	0.00893*** (0.000935)	0.00933*** (0.000953)	0.00938*** (0.000956)	0.00935*** (0.000957)
PointsBA	-0.00304** (0.000950)	-0.00326*** (0.000969)	-0.00323*** (0.000973)	-0.00321*** (0.000973)
Pointsdiff	0.000592 (0.00141)	0.000604 (0.00144)	0.000556 (0.00144)	0.000588 (0.00144)
Opening	0.194*** (0.0354)	0.195*** (0.0361)	0.202*** (0.0363)	0.200*** (0.0363)
Weekend	0.105*** (0.0192)	0.105*** (0.0196)	0.109*** (0.0197)	0.108*** (0.0197)
Holidays	0.352*** (0.0604)	0.362*** (0.0616)	0.367*** (0.0618)	0.368*** (0.0618)
Temp	-0.0000881 (0.00119)	-0.000277 (0.00121)	-0.000192 (0.00122)	-0.000233 (0.00122)
Tempwarm	-0.000656* (0.000332)	-0.000706* (0.000339)	-0.000739* (0.000340)	-0.000714* (0.000341)
Precip	-0.0820*** (0.0237)	-0.0817*** (0.0242)	-0.0835*** (0.0243)	-0.0835*** (0.0243)
StadiumAge	-0.00187*** (0.000356)	-0.00155*** (0.000361)	-0.00150*** (0.000365)	-0.00157*** (0.000364)
ClubAgeH	-0.0285*** (0.00171)	-0.0271*** (0.00174)	-0.0271*** (0.00175)	-0.0271*** (0.00174)
PlayoffsH	0.0779*** (0.0168)	0.0789*** (0.0171)	0.0838*** (0.0174)	0.0781*** (0.0174)
PlayoffsA	0.0299 (0.0163)	0.0292 (0.0166)	0.0310 (0.0168)	0.0265 (0.0168)
ChampH	0.0891** (0.0306)	0.104*** (0.0312)	0.124*** (0.0315)	0.115*** (0.0316)
ChampA	0.0409 (0.0302)	0.0613* (0.0308)	0.0868** (0.0312)	0.0755* (0.0311)
Population	2.20e-09 (1.53e-09)	4.43e-09** (1.56e-09)	4.10e-09** (1.56e-09)	4.16e-09** (1.56e-09)
Income	0.00000542*** (0.00000137)	0.00000416** (0.00000139)	0.00000421** (0.00000140)	0.00000439** (0.00000140)
_cons	9.225*** (0.0965)	9.303*** (0.0989)	9.392*** (0.0976)	9.384*** (0.0975)
N	2201	2201	2201	2201
R-sq	0.272	0.242	0.236	0.236
adj. R-sq	0.262	0.233	0.226	0.226

Source: Same as Table 3.1

Note: Values in parentheses are the standard errors. Main independent variables (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) stand for aggregate number of star players. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.3

Regression Results of Star Players (Dependent Var. ATTper)

Dependent Var.	ATTper	ATTper	ATTper	ATTper
Top10Sal	0.0371*** (0.00845)			
Top30Sal		0.0133** (0.00500)		
Awards			-0.0122 (0.00640)	
AllStars				0.00501 (0.00422)
PointsBH	0.00494*** (0.000694)	0.00506*** (0.000695)	0.00507*** (0.000695)	0.00506*** (0.000696)
PointsBA	-0.000383 (0.000705)	-0.000465 (0.000706)	-0.000435 (0.000706)	-0.000435 (0.000707)
Pointsdiff	0.000970 (0.00104)	0.000985 (0.00105)	0.000933 (0.00105)	0.000984 (0.00105)
Opening	0.169*** (0.0262)	0.168*** (0.0263)	0.171*** (0.0263)	0.169*** (0.0264)
Weekend	0.0805*** (0.0141)	0.0799*** (0.0141)	0.0817*** (0.0141)	0.0810*** (0.0141)
Holidays	0.323*** (0.0488)	0.325*** (0.0488)	0.325*** (0.0487)	0.327*** (0.0489)
Temp	0.00214* (0.000872)	0.00205* (0.000874)	0.00208* (0.000874)	0.00205* (0.000876)
Tempwarm	-0.00101*** (0.000244)	-0.00102*** (0.000244)	-0.00104*** (0.000244)	-0.00102*** (0.000245)
Precip	-0.0373* (0.0172)	-0.0370* (0.0173)	-0.0380* (0.0173)	-0.0379* (0.0173)
StadiumAge	-0.00193*** (0.000263)	-0.00182*** (0.000263)	-0.00176*** (0.000265)	-0.00184*** (0.000264)
ClubAgeH	-0.00497*** (0.00126)	-0.00451*** (0.00126)	-0.00442*** (0.00126)	-0.00450*** (0.00126)
PlayoffsH	0.0470*** (0.0123)	0.0470*** (0.0123)	0.0517*** (0.0125)	0.0456*** (0.0125)
PlayoffsA	0.0196 (0.0120)	0.0193 (0.0120)	0.0218 (0.0121)	0.0169 (0.0121)
ChampH	0.0686** (0.0226)	0.0717** (0.0227)	0.0832*** (0.0227)	0.0737** (0.0228)
ChampA	0.0184 (0.0221)	0.0219 (0.0222)	0.0376 (0.0223)	0.0253 (0.0224)
Population	-1.58e-08*** (1.12e-09)	-1.51e-08*** (1.12e-09)	-1.53e-08*** (1.12e-09)	-1.52e-08*** (1.12e-09)
Income	0.00000733*** (0.00000102)	0.00000692*** (0.00000102)	0.00000685*** (0.00000102)	0.00000705*** (0.00000102)
_cons	-0.00660 (0.0713)	0.00878 (0.0718)	0.0531 (0.0706)	0.0432 (0.0706)
sigma_cons	0.252*** (0.00438)	0.253*** (0.00439)	0.253*** (0.00439)	0.253*** (0.00440)
N	2201	2201	2201	2201
pseudo R-sq	0.523	0.521	0.522	0.520

Source: Same as Table 3.1

Note: Ratio of match attendance to stadium capacity (*ATTper*) is censored when it is larger than 1. Values in parentheses are the standard errors. Main independent variables (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) stand for aggregate number of star players. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.4

Marginal Ticket Revenue Generated by Top-10 Paid Players

Year	Ave. Salary	Percentage Change (previous year)	Rounds	Marginal Ticket Revenue	Difference
2004	293,558.81		30	3,283,468.80	2,989,909.99
2005	374,650.51	27.62366423	32	3,502,366.72	3,127,716.21
2006	405,781.95	8.30946153	32	3,502,366.72	3,096,584.77
2007	1,093,167.31	169.3977172	30	3,283,468.80	2,190,301.49
2008	1,224,772.39	12.03887811	30	3,283,468.80	2,058,696.41
2009	1,414,936.37	15.52647509	30	3,283,468.80	1,868,532.43
2010	1,822,226.18	28.78502657	30	3,283,468.80	1,461,242.62
2011	2,171,677.99	19.17719182	34	3,721,264.64	1,549,586.65
2012	1,766,424.10	-18.66086463	34	3,721,264.64	1,954,840.54
2013	1,525,888.39	-13.61709852	34	3,721,264.64	2,195,376.25
2014	3,094,865.63	102.8238533	34	3,721,264.64	626,399.01
AVE	1,380,722.69			3,482,466.91	

Note: Marginal Ticket Revenue was roughly calculated by the product of average salary and the coefficient for *Top10Sal* (2,092) in Table 4.1. The calculation of average salary excluded players on Canadian clubs. Percentage Change stands for percentage change based on the previous season. Difference stands for the difference between marginal ticket revenue and average salary.

Table 4.5

Home and Away Regression Results of Star Players (Dependent Var. Attendance)

Dependent Var.	Attendance	Attendance	Attendance	Attendance
Top10SalH	2321.1*** (336.7)			
Top10SalA	2409.1*** (317.5)			
Top30SalH		304.4 (204.9)		
Top30SalA		637.6** (197.8)		
AwardsH			-454.0 (251.6)	
AwardsA			335.2 (251.4)	
AllStarsH				-233.7 (169.0)
AllStarsA				396.6* (164.8)
PointsBH	169.3*** (19.20)	178.2*** (19.51)	180.9*** (19.57)	181.9*** (19.58)
PointsBA	-68.93*** (19.49)	-73.89*** (19.83)	-75.67*** (19.90)	-76.95*** (19.91)
Pointsdiff	18.55 (28.78)	18.40 (29.37)	17.97 (29.42)	19.37 (29.42)
Opening	2661.7*** (724.1)	2711.7*** (739.3)	2817.6*** (740.1)	2820.7*** (740.6)
Weekend	934.1* (393.4)	950.9* (401.8)	1011.5* (402.0)	1034.0* (402.2)
Holidays	5709.8*** (1236.0)	5988.3*** (1261.2)	6031.9*** (1262.2)	6059.2*** (1261.3)
Temp	-19.31 (24.29)	-22.40 (24.79)	-19.15 (24.84)	-20.24 (24.86)
Tempwarm	-10.31 (6.793)	-11.48 (6.927)	-12.65 (6.948)	-11.80 (6.947)
Precip	-1409.9** (484.3)	-1407.6** (494.2)	-1428.9** (495.0)	-1401.9** (494.9)
StadiumAge	-35.31*** (7.306)	-29.01*** (7.391)	-26.70*** (7.505)	-27.97*** (7.434)
ClubAgeH	-598.6*** (35.04)	-571.4*** (35.51)	-566.8*** (35.74)	-577.5*** (35.64)
PlayoffsH	1418.5*** (342.7)	1458.8*** (349.9)	1594.4*** (358.3)	1567.9*** (358.3)
PlayoffsA	664.0* (332.9)	641.1 (339.4)	560.0 (345.1)	510.9 (344.2)
ChampH	737.0 (630.0)	1166.1 (642.4)	1542.7* (648.8)	1498.6* (650.5)
ChampA	695.7 (621.8)	1110.8 (635.1)	1273.8* (646.4)	1111.9 (644.3)
Population	0.0000163 (0.0000317)	0.0000563 (0.0000319)	0.0000528 (0.0000318)	0.0000500 (0.0000319)
Income	0.179*** (0.0281)	0.156*** (0.0285)	0.152*** (0.0287)	0.154*** (0.0286)
_cons	9332.1*** (1971.9)	11228.2*** (2024.0)	12518.2*** (1992.0)	12582.9*** (1988.2)
N	2201	2201	2201	2201
R-sq	0.232	0.200	0.198	0.199
adj. R-sq	0.222	0.190	0.187	0.188

Source: Same as Table 3.1

Note: Values in parentheses are the standard errors. Main independent variables (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) stand for individual number of star players for both home and away team. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.6

Home and Away Regression Results of Star Players (Dependent Var. LnATT)

Dependent Var.	LnATT	LnATT	LnATT	LnATT
Top10SalH	0.122*** (0.0165)			
Top10SalA	0.114*** (0.0155)			
Top30SalH		0.0305** (0.0100)		
Top30SalA		0.0299** (0.00967)		
AwardsH			-0.0268* (0.0123)	
AwardsA			0.00562 (0.0123)	
AllStarsH				-0.00282 (0.00829)
AllStarsA				0.0122 (0.00808)
PointsBH	0.00889*** (0.000939)	0.00933*** (0.000954)	0.00950*** (0.000958)	0.00946*** (0.000960)
PointsBA	-0.00301** (0.000953)	-0.00326*** (0.000970)	-0.00336*** (0.000975)	-0.00333*** (0.000976)
Pointsdiff	0.000597 (0.00141)	0.000605 (0.00144)	0.000566 (0.00144)	0.000610 (0.00144)
Opening	0.194*** (0.0354)	0.195*** (0.0361)	0.202*** (0.0362)	0.201*** (0.0363)
Weekend	0.105*** (0.0192)	0.105*** (0.0196)	0.109*** (0.0197)	0.109*** (0.0197)
Holidays	0.351*** (0.0605)	0.362*** (0.0617)	0.368*** (0.0618)	0.369*** (0.0618)
Temp	-0.0000914 (0.00119)	-0.000278 (0.00121)	-0.000106 (0.00122)	-0.000187 (0.00122)
Tempwarm	-0.000651 (0.000332)	-0.000706* (0.000339)	-0.000774* (0.000340)	-0.000722* (0.000341)
Precip	-0.0819*** (0.0237)	-0.0817*** (0.0242)	-0.0831*** (0.0242)	-0.0827*** (0.0243)
StadiumAge	-0.00188*** (0.000357)	-0.00155*** (0.000361)	-0.00142*** (0.000368)	-0.00153*** (0.000364)
ClubAgeH	-0.0286*** (0.00171)	-0.0271*** (0.00174)	-0.0268*** (0.00175)	-0.0273*** (0.00175)
PlayoffsH	0.0779*** (0.0168)	0.0789*** (0.0171)	0.0882*** (0.0175)	0.0815*** (0.0176)
PlayoffsA	0.0297 (0.0163)	0.0292 (0.0166)	0.0276 (0.0169)	0.0245 (0.0169)
ChampH	0.0877** (0.0308)	0.104*** (0.0314)	0.132*** (0.0318)	0.121*** (0.0319)
ChampA	0.0424 (0.0304)	0.0615* (0.0311)	0.0761* (0.0317)	0.0684* (0.0316)
Population	2.12e-09 (1.55e-09)	4.44e-09** (1.56e-09)	4.07e-09** (1.56e-09)	4.05e-09** (1.56e-09)
Income	0.00000547*** (0.00000137)	0.00000416** (0.00000139)	0.00000403** (0.00000140)	0.00000427** (0.00000140)
_cons	9.225*** (0.0965)	9.303*** (0.0990)	9.388*** (0.0975)	9.385*** (0.0975)
N	2201	2201	2201	2201
R-sq	0.272	0.242	0.238	0.237
adj. R-sq	0.262	0.232	0.227	0.226

Source: Same as Table 3.1

Note: Values in parentheses are the standard errors. Main independent variables (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) stand for individual number of star players for both home and away teams. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.7

Home and Away Regression Results of Star Players (Dependent Var. ATTper)

Dependent Var.	ATTper	ATTper	ATTper	ATTper
Top10SalH	0.0115 (0.0121)			
Top10SalA	0.0607*** (0.0116)			
Top30SalH		0.0120 (0.00717)		
Top30SalA		0.0146* (0.00694)		
AwardsH			-0.0301*** (0.00883)	
AwardsA			0.00547 (0.00881)	
AllStarsH				0.00701 (0.00599)
AllStarsA				0.00315 (0.00579)
PointsBH	0.00513*** (0.000696)	0.00507*** (0.000695)	0.00520*** (0.000694)	0.00503*** (0.000698)
PointsBA	-0.000560 (0.000707)	-0.000473 (0.000707)	-0.000584 (0.000706)	-0.000405 (0.000710)
Pointsdiff	0.000962 (0.00104)	0.000984 (0.00105)	0.000967 (0.00104)	0.000975 (0.00105)
Opening	0.169*** (0.0262)	0.168*** (0.0263)	0.171*** (0.0262)	0.169*** (0.0264)
Weekend	0.0807*** (0.0141)	0.0799*** (0.0141)	0.0818*** (0.0141)	0.0808*** (0.0141)
Holidays	0.328*** (0.0487)	0.325*** (0.0488)	0.325*** (0.0486)	0.327*** (0.0489)
Temp	0.00215* (0.000870)	0.00206* (0.000874)	0.00217* (0.000872)	0.00204* (0.000876)
Tempwarm	-0.00104*** (0.000244)	-0.00103*** (0.000244)	-0.00108*** (0.000244)	-0.00102*** (0.000245)
Precip	-0.0381* (0.0172)	-0.0369* (0.0173)	-0.0375* (0.0172)	-0.0381* (0.0173)
StadiumAge	-0.00185*** (0.000264)	-0.00182*** (0.000263)	-0.00167*** (0.000266)	-0.00185*** (0.000265)
ClubAgeH	-0.00462*** (0.00126)	-0.00452*** (0.00126)	-0.00422*** (0.00126)	-0.00446*** (0.00126)
PlayoffsH	0.0468*** (0.0123)	0.0472*** (0.0124)	0.0565*** (0.0126)	0.0447*** (0.0126)
PlayoffsA	0.0209 (0.0120)	0.0193 (0.0120)	0.0181 (0.0121)	0.0174 (0.0122)
ChampH	0.0763*** (0.0227)	0.0723** (0.0228)	0.0920*** (0.0229)	0.0721** (0.0231)
ChampA	0.0104 (0.0222)	0.0212 (0.0223)	0.0263 (0.0226)	0.0271 (0.0227)
Population	-1.54e-08*** (1.13e-09)	-1.52e-08*** (1.12e-09)	-1.53e-08*** (1.11e-09)	-1.52e-08*** (1.12e-09)
Income	0.00000706*** (0.00000102)	0.00000692*** (0.00000102)	0.00000664*** (0.00000102)	0.00000708*** (0.00000102)
_cons	-0.00536 (0.0712)	0.00858 (0.0718)	0.0509 (0.0704)	0.0427 (0.0707)
sigma_cons	0.252*** (0.00437)	0.253*** (0.00439)	0.252*** (0.00438)	0.253*** (0.00440)
N	2201	2201	2201	2201
pseudo R-sq	0.534	0.524	0.526	0.521

Source: Same as Table 3.1

Note: Values in parentheses are the standard errors. Main independent variables (*Top10Sal*, *Top30Sal*, *Awards*, and *AllStars*) stand for individual number of star players for both home and away team. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.8

Results of Testing for Equality (Superstar Externality)

Model	**Variable**	H_0	**F-value**	**Prob>F**	**Interpretation** ($\alpha = 0.05$)
Attendance	*Top10Sal*	Top10SalH=Top10SalA	F(1, 2171) = 0.04	0.8476	Do not reject the null
	Top30Sal	Top30SalH=Top30SalA	F(1, 2171) = 1.38	0.2407	Do not reject the null
LnATT	*Top10Sal*	Top10SalH=Top10SalA	F(1, 2171) = 0.15	0.7027	Do not reject the null
	Top30Sal	Top30SalH=Top30SalA	F(1, 2171) = 0.00	0.9624	Do not reject the null

Table 4.9

Results of Testing for Joint Significance (Superstar Externality)

Model	Variable	H_0	F-value	Prob>F	Interpretation ($\alpha = 0.05$)
Attendance	*Top10Sal*	Top10SalH=0 Top10SalA=0	F(2, 2171) = 51.36	0.0000	Reject
	Top30Sal	Top30SalH=0 Top30SalA=0	F(2, 2171) = 6.27	0.0019	Reject
LnATT	*Top10Sal*	Top10SalH=0 Top10SalA=0	F(2, 2171) = 53.26	0.0000	Reject
	Top30Sal	Top30SalH=0 Top30SalA=0	F(2, 2171) = 9.34	0.0001	Reject

Table 4.10

Aggregate Regression Results of International Players

Dependent Var.	Attendance	LnATT	ATTper
Inter	223.8*** (61.46)	0.0122*** (0.00301)	0.0147*** (0.00216)
PointsBH	177.4*** (19.48)	0.00935*** (0.000953)	0.00501*** (0.000688)
PointsBA	-73.53*** (19.81)	-0.00329*** (0.000969)	-0.000466 (0.000700)
Pointsdiff	19.18 (29.36)	0.000628 (0.00144)	0.000953 (0.00104)
Opening	2821.3*** (738.5)	0.202*** (0.0361)	0.171*** (0.0261)
Weekend	1054.8** (401.4)	0.111*** (0.0196)	0.0848*** (0.0140)
Holidays	6057.0*** (1259.4)	0.370*** (0.0616)	0.329*** (0.0483)
Temp	-14.98 (24.83)	0.000158 (0.00122)	0.00250** (0.000868)
Tempwarm	-12.74 (6.927)	-0.000784* (0.000339)	-0.00111*** (0.000242)
Precip	-1458.9** (494.0)	-0.0846*** (0.0242)	-0.0393* (0.0171)
StadiumAge	-28.14*** (7.392)	-0.00150*** (0.000362)	-0.00172*** (0.000262)
ClubAgeH	-571.2*** (35.49)	-0.0271*** (0.00174)	-0.00450*** (0.00125)
PlayoffsH	1468.1*** (349.5)	0.0804*** (0.0171)	0.0482*** (0.0122)
PlayoffsA	590.5 (339.4)	0.0262 (0.0166)	0.0162 (0.0119)
ChampH	1562.1* (639.0)	0.132*** (0.0313)	0.0944*** (0.0225)
ChampA	1844.2** (631.3)	0.0990** (0.0309)	0.0535* (0.0221)
Population	0.0000349 (0.0000322)	3.08e-09 (1.57e-09)	-1.65e-08*** (1.12e-09)
Income	0.167*** (0.0286)	0.00000484*** (0.00000140)	0.00000755*** (0.00000101)
_cons	10277.6*** (2082.0)	9.261*** (0.102)	-0.104 (0.0733)
sigma_cons			0.251*** (0.00435)
N	2201	2201	2201
R-sq	0.201	0.241	
adj. R-sq	0.190	0.232	
pseudo R-sq			0.544

Source: Same as Table 3.1

Note: Three specifications of match attendance. Ratio of match attendance to stadium capacity (*ATTper*) is censored when it is larger than 1. Values in parentheses are the standard errors. The main independent variable (*Inter*) stands for aggregate number of international players. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.11

Home and Away Regression Results of International Players

Dependent Var.	Attendance	LnATT	ATTper
InterH	415.9*** (84.88)	0.0218*** (0.00415)	0.0214*** (0.00299)
InterA	38.92 (83.37)	0.00296 (0.00408)	0.00831** (0.00292)
PointsBH	173.4*** (19.48)	0.00915*** (0.000953)	0.00487*** (0.000688)
PointsBA	-70.29*** (19.79)	-0.00312** (0.000968)	-0.000350 (0.000699)
Pointsdiff	20.09 (29.30)	0.000673 (0.00143)	0.000990 (0.00103)
Opening	2884.2*** (737.1)	0.205*** (0.0361)	0.174*** (0.0260)
Weekend	1088.3** (400.6)	0.113*** (0.0196)	0.0857*** (0.0140)
Holidays	6155.2*** (1257.0)	0.375*** (0.0615)	0.331*** (0.0481)
Temp	-8.768 (24.85)	0.000467 (0.00122)	0.00272** (0.000869)
Tempwarm	-13.89* (6.921)	-0.000841* (0.000339)	-0.00115*** (0.000242)
Precip	-1441.0** (492.9)	-0.0837*** (0.0241)	-0.0386* (0.0171)
StadiumAge	-26.83*** (7.386)	-0.00143*** (0.000361)	-0.00165*** (0.000263)
ClubAgeH	-569.7*** (35.42)	-0.0270*** (0.00173)	-0.00447*** (0.00124)
PlayoffsH	1475.1*** (348.7)	0.0807*** (0.0171)	0.0486*** (0.0122)
PlayoffsA	615.2 (338.8)	0.0275 (0.0166)	0.0168 (0.0119)
ChampH	1802.8** (641.8)	0.144*** (0.0314)	0.103*** (0.0226)
ChampA	1613.5* (633.8)	0.0875** (0.0310)	0.0457* (0.0222)
Population	0.0000205 (0.0000324)	2.37e-09 (1.59e-09)	-1.70e-08*** (1.13e-09)
Income	0.170*** (0.0285)	0.00000499*** (0.00000140)	0.00000761*** (0.00000101)
_cons	9740.4*** (2083.8)	9.234*** (0.102)	-0.122 (0.0733)
sigma_cons			0.250*** (0.00434)
N	2201	2201	2201
R-sq	0.205	0.245	
adj. R-sq	0.194	0.235	
pseudo R-sq			0.549

Source: Same as Table 3.1

Note: Three specifications of match attendance. Ratio of match attendance to stadium capacity (*ATTper*) is censored when it is larger than 1. Values in parentheses are the standard errors. Main independent variable (*Inter*) stands for individual number of international players for both home and away team. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.12

Regression Results of International Players by Confederations

Dependent Var.	Attendance	LnATT	ATTper
Africa	315.3* (128.5)	0.0209*** (0.00628)	0.0174*** (0.00454)
Asia	1511.3*** (351.3)	0.0729*** (0.0172)	0.0500*** (0.0126)
Europe	208.2 (116.7)	0.0145* (0.00570)	0.00913* (0.00413)
Central	120.4 (98.56)	0.00118 (0.00481)	0.0166*** (0.00346)
South	165.8 (90.86)	0.00996* (0.00444)	0.0122*** (0.00319)
Oceania	-102.5 (471.4)	-0.00681 (0.0230)	0.0341* (0.0163)
PointsBH	174.4*** (19.46)	0.00916*** (0.000951)	0.00500*** (0.000688)
PointsBA	-75.28*** (19.77)	-0.00342*** (0.000966)	-0.000466 (0.000699)
Pointsdiff	18.20 (29.52)	0.000813 (0.00144)	0.000614 (0.00104)
Opening	2791.2*** (736.8)	0.201*** (0.0360)	0.171*** (0.0260)
Weekend	1072.1** (400.6)	0.112*** (0.0196)	0.0854*** (0.0140)
Holidays	5827.3*** (1257.6)	0.357*** (0.0614)	0.325*** (0.0483)
Temp	-12.15 (24.86)	0.000419 (0.00121)	0.00250** (0.000870)
Tempwarm	-13.02 (6.946)	-0.000844* (0.000339)	-0.00107*** (0.000243)
Precip	-1438.2** (493.9)	-0.0851*** (0.0241)	-0.0369* (0.0171)
StadiumAge	-27.97*** (7.491)	-0.00151*** (0.000366)	-0.00172*** (0.000265)
ClubAgeH	-586.2*** (35.81)	-0.0281*** (0.00175)	-0.00464*** (0.00126)
PlayoffsH	1455.6*** (349.4)	0.0794*** (0.0171)	0.0492*** (0.0122)
PlayoffsA	556.8 (339.4)	0.0240 (0.0166)	0.0176 (0.0119)
ChampH	1230.7 (645.4)	0.112*** (0.0315)	0.0905*** (0.0227)
ChampA	1494.1* (640.6)	0.0770* (0.0313)	0.0503* (0.0224)
Population	0.0000319 (0.0000326)	2.86e-09 (1.59e-09)	-1.64e-08*** (1.14e-09)
Income	0.156*** (0.0291)	0.00000435** (0.00000142)	0.00000746*** (0.00000103)
_cons	11209.5*** (2106.5)	9.315*** (0.103)	-0.109 (0.0742)
sigma_cons			0.250*** (0.00434)
N	2201	2201	2201
R-sq	0.207	0.250	
adj. R-sq	0.195	0.238	
pseudo R-sq			0.550

Source: Same as Table 3.1

Note: Three specifications of match attendance. Ratio of match attendance to stadium capacity (*ATTper*) is censored when it is larger than 1. Values in parentheses are the standard errors. Main independent variable (*Inter*) stands for individual number of international players for both home and away team. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.13

List of Top-10 Paid and DP Players by Year since the 2007 Season

Season	Names of Top-10 Paid Players
2007	**David Beckham***, **Cuauhtémoc Blanco***, **Juan Pablo Ángel***, Claudio Reyna, Landon Donovan, **Denílson***, Eddie Johnson, Taylor Twellman, Carlos Ruiz*, Dwayne De Rosario
2008	**David Beckham***, **Cuauhtémoc Blanco***, **Marcelo Gallardo***, **Juan Pablo Ángel***, Landon Donovan, **Luciano Emilio***, **Claudio López***, Duilio Davino*, Christian Gomez*, Carlos Ruiz*
2009	**David Beckham***, **Cuauhtémoc Blanco***, **Juan Pablo Ángel***, **Freddie Ljungberg***, Julian de Guzman, Landon Donovan, **Luciano Emilio***, **Guillermo Barros Schelotto***, Shalrie Joseph*, Taylor Twellman
2010	**Rafael Márquez***, **David Beckham***, **Thierry Henry***, Landon Donovan, Julian de Guzman, **Juan Pablo Ángel***, **Nery Castillo***, **Freddie Ljungberg***, **Mista***, **Blaise Nkufo***
2011	**David Beckham***, **Thierry Henry***, **Rafael Márquez***, **Robbie Keane***, Landon Donovan, Julian de Guzman, **Juan Pablo Ángel***, **Danny Koevermans***, **Torsten Frings***, **Eric Hassli***
2012	**Thierry Henry***, **Rafael Márquez***, **David Beckham***, **Robbie Keane***, Landon Donovan, **Torsten Frings***, Julian de Guzman, **Kris Boyd***, **Danny Koevermans***, Dwayne De Rosario
2013	**Robbie Keane***, **Thierry Henry***, **Tim Cahill***, Landon Donovan, **Obafemi Martins***, **Danny Koevermans***, **Kenny Miller***, **Marco Di Vaio***, **Fredy Montero***, **David Ferreira***
2014	Michael Bradley, **Jermain Defoe***, Clint Dempsey, **Robbie Keane***, Landon Donovan, **Thierry Henry***, **Tim Cahill***, **Obafemi Martins***, **Marco Di Vaio***, **Pedro Morales***

Source: Designated Players from MLS's official website, [http://www.mlssoccer.com]. Player's salary information from MLS Player's Union website, [http://www.mlsplayers.org].

Note: Bold names indicate the DPs. * indicates foreign-born players

Figure 4.1

QQ Plot for Testing Normal Distribution (Attendance)

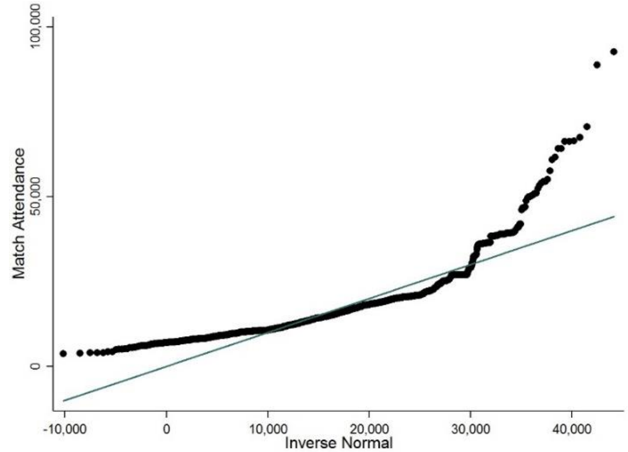


Figure 4.2

QQ Plot for Testing Normal Distribution (LnATT)

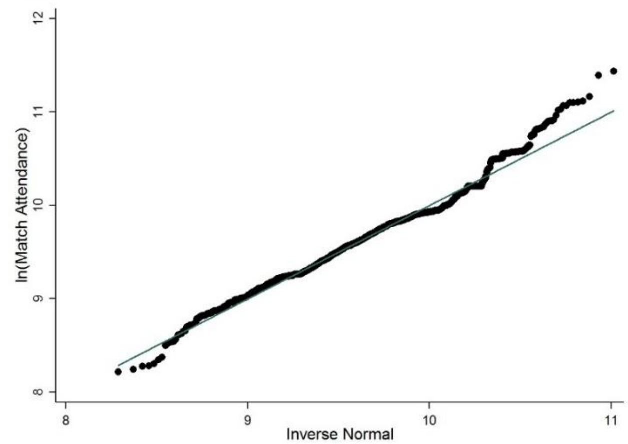
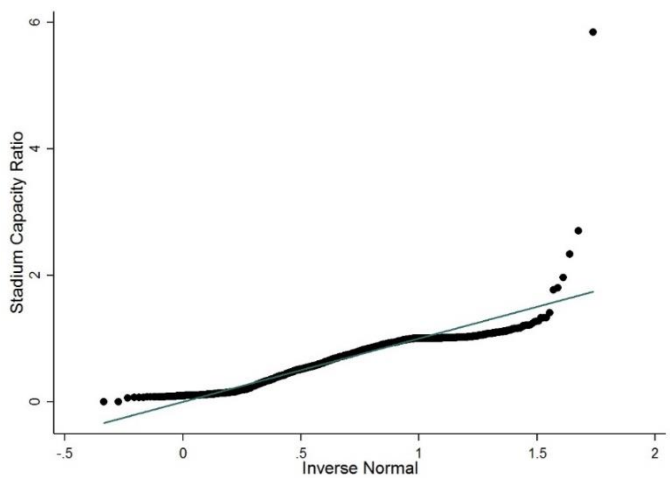


Figure 4.3

QQ Plot for Testing Normal Distribution (ATTper)



APPENDICES

Appendix (A) Exclusion of David Beckham

Table A-1

Regression Results after Excluding David Beckham

Dependent Var.	Attendance	Attendance	Attendance	Attendance
Top10Sal	1968.9*** (265.6)			
Top30Sal		196.4 (147.1)		
Awards			-140.7 (185.3)	
AllStars				1.391 (122.3)
PointsBH	171.6*** (19.31)	177.6*** (19.53)	177.9*** (19.54)	177.7*** (19.54)
PointsBA	-69.28*** (19.63)	-72.57*** (19.86)	-72.40*** (19.87)	-72.31*** (19.87)
Pointsdiff	21.44 (29.09)	18.36 (29.44)	17.88 (29.45)	17.69 (29.46)
Opening	2735.5*** (731.6)	2770.5*** (740.8)	2815.7*** (740.8)	2802.7*** (741.6)
Weekend	931.5* (397.5)	980.2* (402.7)	1007.1* (402.4)	1006.5* (402.6)
Holidays	5831.5*** (1247.8)	5983.2*** (1262.9)	5996.0*** (1263.2)	6009.9*** (1263.2)
Temp	-18.08 (24.54)	-21.65 (24.84)	-21.40 (24.85)	-21.18 (24.88)
Tempwarm	-11.53 (6.857)	-11.71 (6.941)	-11.85 (6.943)	-11.77 (6.954)
Precip	-1425.7** (489.3)	-1426.8** (495.3)	-1437.3** (495.4)	-1437.2** (495.5)
StadiumAge	-34.13*** (7.350)	-29.04*** (7.407)	-28.40*** (7.458)	-29.06*** (7.427)
ClubAgeH	-586.8*** (35.21)	-571.3*** (35.60)	-570.7*** (35.69)	-572.7*** (35.65)
PlayoffsH	1415.6*** (346.3)	1457.5*** (350.5)	1513.7*** (355.7)	1467.2*** (355.3)
PlayoffsA	622.8 (336.1)	631.7 (340.2)	665.1 (343.5)	628.6 (343.7)
ChampH	896.6 (631.8)	1227.3 (640.1)	1369.4* (641.6)	1310.9* (642.2)
ChampA	919.7 (623.0)	1382.1* (631.5)	1579.4* (635.4)	1495.0* (634.2)
Population	0.0000335 (0.0000316)	0.0000569 (0.0000320)	0.0000534 (0.0000319)	0.0000536 (0.0000319)
Income	0.169*** (0.0282)	0.156*** (0.0286)	0.156*** (0.0286)	0.157*** (0.0286)
_cons	9880.6*** (1999.3)	12028.1*** (2030.4)	12648.9*** (1993.6)	12565.5*** (1991.5)
N	2201	2201	2201	2201
R-sq	0.216	0.197	0.196	0.196
adj. R-sq	0.206	0.186	0.186	0.186

Source: Same as Table 3.1

Table A-2

Regression Results after Excluding David Beckham

Dependent Var.	LnATT	LnATT	LnATT	LnATT
Top10Sal	0.0988*** (0.0130)			
Top30Sal		0.0168* (0.00719)		
Awards			-0.0140 (0.00907)	
AllStars				0.00109 (0.00599)
PointsBH	0.00906*** (0.000945)	0.00936*** (0.000956)	0.00938*** (0.000956)	0.00936*** (0.000957)
PointsBA	-0.00307** (0.000960)	-0.00324*** (0.000972)	-0.00323*** (0.000972)	-0.00322*** (0.000973)
Pointsdiff	0.000735 (0.00142)	0.000604 (0.00144)	0.000566 (0.00144)	0.000554 (0.00144)
Opening	0.198*** (0.0358)	0.198*** (0.0362)	0.202*** (0.0363)	0.201*** (0.0363)
Weekend	0.105*** (0.0195)	0.107*** (0.0197)	0.109*** (0.0197)	0.109*** (0.0197)
Holidays	0.359*** (0.0611)	0.365*** (0.0618)	0.366*** (0.0618)	0.368*** (0.0619)
Temp	-0.0000241 (0.00120)	-0.000220 (0.00122)	-0.000203 (0.00122)	-0.000190 (0.00122)
Tempwarm	-0.000719* (0.000336)	-0.000726* (0.000340)	-0.000739* (0.000340)	-0.000728* (0.000340)
Precip	-0.0829*** (0.0239)	-0.0826*** (0.0242)	-0.0835*** (0.0242)	-0.0835*** (0.0243)
StadiumAge	-0.00180*** (0.000360)	-0.00155*** (0.000362)	-0.00148*** (0.000365)	-0.00155*** (0.000364)
ClubAgeH	-0.0279*** (0.00172)	-0.0271*** (0.00174)	-0.0270*** (0.00175)	-0.0272*** (0.00175)
PlayoffsH	0.0777*** (0.0169)	0.0795*** (0.0171)	0.0849*** (0.0174)	0.0798*** (0.0174)
PlayoffsA	0.0280 (0.0164)	0.0286 (0.0166)	0.0319 (0.0168)	0.0279 (0.0168)
ChampH	0.0976** (0.0309)	0.111*** (0.0313)	0.124*** (0.0314)	0.118*** (0.0314)
ChampA	0.0511 (0.0305)	0.0703* (0.0309)	0.0883** (0.0311)	0.0791* (0.0311)
Population	3.09e-09* (1.55e-09)	4.38e-09** (1.56e-09)	4.09e-09** (1.56e-09)	4.11e-09** (1.56e-09)
Income	0.00000492*** (0.00000138)	0.00000418** (0.00000140)	0.00000418** (0.00000140)	0.00000434** (0.00000140)
_cons	9.251*** (0.0978)	9.340*** (0.0993)	9.394*** (0.0976)	9.385*** (0.0975)
N	2201	2201	2201	2201
R-sq	0.256	0.238	0.237	0.236
adj. R-sq	0.246	0.228	0.227	0.226

Source: Same as Table 3.1

Table A-3

Regression Results after Excluding David Beckham

Dependent Var.	ATTper	ATTper	ATTper	ATTper
Top10Sal	0.0174 (0.00942)			
Top30Sal		0.00549 (0.00514)		
Awards			-0.0138* (0.00649)	
AllStars				0.00356 (0.00430)
PointsBH	0.00502*** (0.000696)	0.00507*** (0.000696)	0.00507*** (0.000694)	0.00506*** (0.000696)
PointsBA	-0.000409 (0.000707)	-0.000446 (0.000707)	-0.000436 (0.000706)	-0.000433 (0.000707)
Pointsdiff	0.000973 (0.00105)	0.000961 (0.00105)	0.000940(0.00105)	0.000965 (0.00105)
Opening	0.170*** (0.0263)	0.170*** (0.0263)	0.171*** (0.0263)	0.169*** (0.0264)
Weekend	0.0809*** (0.0141)	0.0808*** (0.0141)	0.0816*** (0.0141)	0.0812*** (0.0141)
Holidays	0.325*** (0.0488)	0.326*** (0.0488)	0.324*** (0.0487)	0.327*** (0.0489)
Temp	0.00213* (0.000875)	0.00209* (0.000875)	0.00208* (0.000874)	0.00207* (0.000876)
Tempwarm	-0.00103*** (0.000245)	-0.00103*** (0.000245)	-0.00104*** (0.000244)	-0.00102*** (0.000245)
Precip	-0.0377* (0.0173)	-0.0375* (0.0173)	-0.0379* (0.0173)	-0.0379* (0.0173)
StadiumAge	-0.00187*** (0.000265)	-0.00182*** (0.000263)	-0.00175*** (0.000265)	-0.00183*** (0.000264)
ClubAgeH	-0.00470*** (0.00126)	-0.00453*** (0.00126)	-0.00441*** (0.00126)	-0.00451*** (0.00126)
PlayoffsH	0.0474*** (0.0124)	0.0475*** (0.0124)	0.0523*** (0.0125)	0.0462*** (0.0125)
PlayoffsA	0.0188 (0.0120)	0.0189 (0.0120)	0.0222 (0.0121)	0.0174 (0.0121)
ChampH	0.0740** (0.0227)	0.0754*** (0.0227)	0.0829*** (0.0227)	0.0753*** (0.0228)
ChampA	0.0251 (0.0222)	0.0268 (0.0222)	0.0380 (0.0223)	0.0270 (0.0223)
Population	-1.55e-08*** (1.12e-09)	-1.52e-08*** (1.12e-09)	-1.53e-08*** (1.12e-09)	-1.52e-08*** (1.12e-09)
Income	0.00000709*** (0.00000102)	0.00000694*** (0.00000102)	0.00000684*** (0.00000102)	0.00000703*** (0.00000102)
_cons	0.0211 (0.0718)	0.0303 (0.0720)	0.0542 (0.0706)	0.0437 (0.0706)
sigma_cons	0.253*** (0.00439)	0.253*** (0.00440)	0.253*** (0.00439)	0.253*** (0.00440)
N	2201	2201	2201	2201

Source: Same as Table 3.1

Table A-4

Comparison the Coefficients for Variables of Interest

Dependent Var.	Attendance		LnATT		ATTper	
	Beckham Included	Beckham Excluded	Beckham Included	Beckham Excluded	Beckham Included	Beckham Excluded
Top10Sal	2367.7***	1968.9***	0.118***	0.0988***	0.0371***	0.0174
Top30Sal	476.9***	196.4	0.0302***	0.0168*	0.0133**	0.00549
Awards	-59.10	-129.7	-0.0106	-0.0135	-0.0122	-0.0135*
AllStars	89.57	40.22	0.00487	0.00259	0.00501	0.00395

Source: Same as Table 3.1

Note: Beckham played 98 games in regular season from 2007 to 2012. Comparing the coefficients for variables of interest, this study found evidence that Beckham effect on match attendance was huge because all coefficients after excluding him from the dataset are lower than those when he is included in.

Appendix (B) Imposition of Categorical Variables (*Top10Sal*)

Table B-1

Regression Results after Excluding David Beckham

Dependent Var.	Attendance	LnATT	ATTper
TopSal1	3613.8*** (442.9)	0.182*** (0.0216)	0.0704*** (0.0159)
TopSal2	5066.5*** (625.4)	0.270*** (0.0306)	0.0903*** (0.0226)
TopSal3	5885.4*** (1163.8)	0.236*** (0.0569)	0.0531 (0.0425)
TopSal4	5681.3** (2094.0)	0.316** (0.102)	0.0694 (0.0733)
PointsBH	167.7*** (19.07)	0.00886*** (0.000932)	0.00490*** (0.000692)
PointsBA	-69.70*** (19.37)	-0.00309** (0.000947)	-0.000410 (0.000703)
Pointsdiff	16.10 (28.72)	0.000420 (0.00140)	0.000903 (0.00104)
Opening	2668.5*** (722.3)	0.196*** (0.0353)	0.169*** (0.0262)
Weekend	981.1* (392.6)	0.108*** (0.0192)	0.0821*** (0.0141)
Holidays	5714.2*** (1231.7)	0.354*** (0.0602)	0.325*** (0.0487)
Temp	-20.61 (24.25)	-0.000105 (0.00119)	0.00212* (0.000870)
Tempwarm	-9.470 (6.783)	-0.000632 (0.000332)	-0.000999*** (0.000244)
Precip	-1449.3** (483.6)	-0.0852*** (0.0236)	-0.0387* (0.0172)
StadiumAge	-34.84*** (7.253)	-0.00184*** (0.000354)	-0.00191*** (0.000263)
ClubAgeH	-603.2*** (34.82)	-0.0287*** (0.00170)	-0.00507*** (0.00126)
PlayoffsH	1450.7*** (341.9)	0.0792*** (0.0167)	0.0477*** (0.0123)
PlayoffsA	645.1 (332.2)	0.0292 (0.0162)	0.0193 (0.0120)
ChampH	689.6 (628.0)	0.0917** (0.0307)	0.0693** (0.0227)
ChampA	543.0 (617.5)	0.0337 (0.0302)	0.0145 (0.0221)
Population	0.0000154 (0.0000313)	2.17e-09 (1.53e-09)	-1.58e-08*** (1.12e-09)
Income	0.180*** (0.0279)	0.00000548*** (0.00000136)	0.00000734*** (0.00000102)
_cons	9408.6*** (1972.4)	9.220*** (0.0964)	-0.00762 (0.0713)
sigma_cons			0.252*** (0.00437)
N	2201	2201	2201
R-sq	0.237	0.278	
adj. R-sq	0.226	0.267	

Note: TopSal1 to TopSal4 stand for categorical variables when one up to four top-10 paid players played at a certain game regardless of home and away team. Games played with no top-10 paid player is a control group. The expected increase in match attendance is the greatest on games played with three top-10 paid players. There is an evidence of diminishing returns since the incremental difference is declining as one more top-10 player added.

Appendix (C) Imposition of Quadratic Form (*Top10Sal*)

Table C-1

Regression Results after Excluding David Beckham

Dependent Var.	Attendance	LnATT	ATTper
Top10Sal	4121.5*** (535.9)	0.214*** (0.0262)	0.0854*** (0.0192)
Top10Sal2	-722.6*** (198.8)	-0.0395*** (0.00972)	-0.0198** (0.00709)
PointsBH	167.6*** (19.06)	0.00886*** (0.000932)	0.00490*** (0.000693)
PointsBA	-69.57*** (19.36)	-0.00309** (0.000947)	-0.000411 (0.000704)
Pointsdiff	15.95 (28.71)	0.000447 (0.00140)	0.000912 (0.00104)
Opening	2674.5*** (721.9)	0.195*** (0.0353)	0.169*** (0.0262)
Weekend	983.6* (392.4)	0.108*** (0.0192)	0.0820*** (0.0141)
Holidays	5718.1*** (1231.3)	0.353*** (0.0602)	0.324*** (0.0487)
Temp	-21.00 (24.22)	-0.000179 (0.00118)	0.00208* (0.000870)
Tempwarm	-9.396 (6.772)	-0.000609 (0.000331)	-0.000988*** (0.000243)
Precip	-1464.1** (483.1)	-0.0851*** (0.0236)	-0.0387* (0.0172)
StadiumAge	-34.78*** (7.250)	-0.00183*** (0.000354)	-0.00191*** (0.000263)
ClubAgeH	-602.6*** (34.80)	-0.0287*** (0.00170)	-0.00507*** (0.00126)
PlayoffsH	1448.9*** (341.8)	0.0796*** (0.0167)	0.0479*** (0.0123)
PlayoffsA	659.7* (331.6)	0.0298 (0.0162)	0.0197 (0.0119)
ChampH	709.8 (623.6)	0.0884** (0.0305)	0.0678** (0.0225)
ChampA	547.3 (616.4)	0.0320 (0.0301)	0.0137 (0.0221)
Population	0.0000163 (0.0000313)	2.25e-09 (1.53e-09)	-1.58e-08*** (1.12e-09)
Income	0.180*** (0.0279)	0.00000547*** (0.00000136)	0.00000734*** (0.00000102)
_cons	9402.0*** (1966.0)	9.229*** (0.0961)	-0.00399 (0.0712)
sigma_cons			0.252*** (0.00437)
N	2201	2201	2201
R-sq	0.237	0.277	
adj. R-sq	0.227	0.267	

Source: Same as Table 3.1

Note: Top10Sal2 represents a quadratic form of Top10Sal. Assumed a quadratic form of Top10Sal, one additional top-10 paid player is expected to increase in match attendance by 3,399 (i.e., $\Delta\text{Attendance} = 4121.5 - 722.6Top10Sal$).

REFERENCES

Adler, M. (1985). Stardom and talent. *American Economic Review*, 75, 208–212.

Becker, G. S. (1971). The Economics of Discrimination 2nd ed (University Of Chicago Press, Chicago).

Berri, D. J., Schmidt, M. B., & Brook, S. L. (2004). Stars at the gate: The impact of star power on NBA gate revenues. *Journal of Sports Economics*, 5, 33–50.

Berri, D. J., & Schmidt, M. B. (2006). On the road with the national basketball association's superstar externality. *Journal of Sports Economics*, 7, 347–358.

Bissonnette, Z. (2014, Dec 5). A sports league that's unprofitable—but hopeful. *CNBC*. Retrieved from http://www.cnbc.com/2014/12/05/major-league-soccer-mls-works-hard-to-become-a-profitable-business.html

Blair, R. D. (2011). *Sports economics*. Cambridge University Press.

Borland, J., & MacDonald, R. (2003). Demand for sport. *Oxford review of economic policy*, 19(4), 478-502.

Brandes, L., Franck, E., & Nüesch, S. (2008). Local heroes and superstars: An empirical analysis of star attraction in German soccer. *Journal of Sports Economics*, 9, 266–286.

Bryant, N. (2015, Jun 2). The myth that America doesn't like football. *BBC*. Retrieved from http://www.bbc.com/news/world-us-canada-32956824

Burdekin, R. C., & Idson, T. L. (1991). Customer preferences, attendance and the racial structure of professional basketball teams. *Applied Economics*, 23(1), 179-186.

Burdekin, R. C., Hossfeld, R. T., & Smith, J. K. (2005). Are NBA fans becoming indifferent to race? Evidence from the 1990s. *Journal of sports economics*, 6(2), 144-159.

Carmichael, F., Thomas, D., & Ward, R. (2001). Production and efficiency in association football. *Journal of sports Economics*, 2(3), 228-243.

Depken, C. A., & Ford, J. M. (2006). Customer-based discrimination against Major League Baseball players: Additional evidence from all-star ballots. *The Journal of Socio-Economics*, 35(6), 1061–1077.

Desser, A., Monks, J., & Robinson, M. (1999). Baseball hall of fame voting: A test of the customer discrimination hypothesis. *Social Science Quarterly*, 80(3), 591–603.

Forrest, D., & Simmons, R. (2002). Outcome uncertainty and attendance demand in sport: the case of English soccer. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 51(2), 229-241.

Fort, R., & Gill, A. (2000). Race and ethnicity assessment in baseball card markets. *Journal of Sports Economics*, 1(1), 21–38.

Franck, E., & Nüesch, S. (2012). Talent and/or popularity: What does it take to be a superstar?

Economic Inquiry, 50, 202–216.

Gwartney, J., & Haworth, C. (1974). Employer costs and discrimination: The case of baseball. *The Journal of Political Economy*, 873-881.

Hanssen, F. A., & Andersen, T. (1999). Has discrimination lessened over time? A test using baseball's all-star vote. *Economic Inquiry*, 37, 326–352.

Hausman, J. A., & Leonard, G. K. (1997). Superstars in the national basketball association: Economic value and policy. *Journal of Labor Economics*, 15, 586–624.

Hersch, P. (2010). Customer discrimination against black Major League Baseball pitchers reconsidered. *Applied Economics Letters*, 17(2), 205–208.

Hoang, H., & Rascher, D. (1999). The NBA, exit discrimination, and career earnings. *Industrial Relations*, 38(1), 69-91.

Humphreys, B. R. (2015). *Economics of Professional Sports*. BRH Publishing.

Jane, W. J. (2014). The Effect of Star Quality on Attendance Demand The Case of the National Basketball Association. *Journal of Sports Economics*, 1527002514530405.

Jewell, R. T. (2015). The Effect of Marquee Players on Sports Demand The Case of US Major League Soccer. *Journal of Sports Economics*, 1527002514567922.

Kahn, L. M. (2000). The sports business as a labor market laboratory. *The Journal of Economic perspectives*, 75-94.

Kanazawa, M. T., & Funk, J. P. (2001). Racial discrimination in professional basketball: Evidence from Nielsen ratings. *Economic Inquiry*, 39(4), 599-608.

Kuethe, T. H., & Motamed, M. (2010). Returns to stardom: Evidence from US major league soccer. *Journal of Sports Economics*, 11, 567–579.

Lawson, R. A., Sheehan, K., & Stephenson, E. F. (2008). Vend it like Beckham: David Beckham's effect on MLS ticket sales. *International Journal of Sport Finance*, 3, 189–195.

LeFeuvre, A. D., Stephenson, E. F., & Walcott, S. M. (2013). Football frenzy: The effect of the 2011 world cup on women's professional soccer league attendance. *Journal of Sports Economics*, 14, 440–448.

Longley, N., Crosset, T., & Jefferson, S. (2008). The migration of African-Americans to the Canadian Football League during the 1950s: An escape from racism?. *The International Journal of the History of Sport*, 25(10), 1374-1397.

Lucifero, C., & Simmons, R. (2003). Superstar effects in sport: Evidence from Italian soccer. *Journal of Sports Economics*, 4, 35–55.

McCormick, R. E., & Tollison, R. D. (2001). Why do black basketball players work more for less money?. *Journal of Economic Behavior & Organization*, 44(2), 201-219.

McGarrity, J., Palmer, H. D., & Poitras, M. (1999). Customer racial discrimination: A reassessment of the market for baseball cards. *Journal of Labor and Research*, 20, 247–259.

Mullin, C. J., & Dunn, L. F. (2002). Using baseball card prices to measure star quality and monopsony. *Economic Inquiry*, 40, 620–632.

Nardinelli, C., & Simon, C. (1990). Customer discrimination in the market for memorabilia: The case of baseball. *The Quarterly Journal of Economics*, 105, 575–595.

Neale, W. C. (1964). The peculiar economics of professional sports: A contribution to the theory of the firm in sporting competition and in market competition. *The Quarterly Journal of Economics*, 1-14.

Noll, R. (1974). Attendance and Price Setting, [w:] Noll R.(eds.), Government and the Sports Business. *Brookings Institute*, *Washington*.

Nüesch, S., & Franck, E. (2009). The role of patriotism in explaining the TV audience of national team games-evidence from four international tournaments. *Journal of Media Economics*, 22, 6–19.

Parrish, C. (2013). Soccer specific stadiums and designated players: Exploring the Major League Soccer attendance assumption. *International Journal of Sport Management Recreation and Tourism*, 12, 57-70.

Pedace, R. (2008). Earnings, performance, and nationality discrimination in a highly competitive labor market as an analysis of the English professional soccer league. *Journal of Sports Economics*, 9(2), 115-140.

Preston, I., & Szymanski, S. (2000). Racial discrimination in English football. *Scottish Journal of Political Economy*, 47(4), 342-363.

Primm, E., Piquero, N. L., Regoli, R. M., & Piquero, A. R. (2010). The Role of Race in Football Card Prices*. *Social Science Quarterly*, 91(1), 129-142.

Rivers, D. H., & DeSchriver, T. D. (2002). Star players, payroll distribution, and Major League Baseball attendance. *Sport Marketing Quarterly*, 11(3), 164-173.

Rosen, S. (1981). The economics of superstars. *The American economic review*, 71(5), 845-858.

Schofield, J. A. (1983). Performance and attendance at professional team sports. *Journal of Sport Behaviour*, 6(4), 196-206.

Scully, G. W. (1974). Pay and performance in major league baseball. *The American Economic Review*, 64(6), 915-930.

Slater, M. (2015, Dec 6). MLS at 20: How football in the USA is thriving at last. *BBC*. Retrieved from http://www.bbc.com/sport/football/35012676

Stone, E. W., & Warren, R. S. (1999). Customer discrimination in professional basketball: Evidence from the trading-card market. *Applied Economics*, 31(6), 679–685.

Smith, C. (2015, Aug 19). Major League Soccer's Most Valuable Teams 2015. *Forbes*. Retrieved from http://www.forbes.com/sites/chrissmith/2015/08/19/major-league-soccers-most-valuable-teams-2015-2/#22ebaee03ba4

Szymanski, S. (2000). A market test for discrimination in the English professional soccer leagues. *Journal of Political Economy*, 108(3), 590-603.

Tainsky, S., & Winfree, J. A. (2010). Discrimination and demand: The effect of international players on attendance in Major League Baseball. *Social Science Quarterly*, 91, 117–128.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica*, 26, 24–36.