To my beloved family and my love
ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my family who has been my enduring believers and supporters. I would also like to thank my love, who has been next to me no matter what. Next, I would like to acknowledge and genuinely appreciate my advisor and mentor, Dr. Brian M. Mills, for his invaluable guidance and care invested in all my works including this dissertation at the University of Florida. It would have been impossible for me to come this far without Dr. Mills, and all the guidance and advice are and will always be one of the most precious lessons I have received in my life. Lastly, I would like to give sincerely gratitude to all my committee members, Dr. Roger Blair, Dr. Yong Jae Ko, and Dr. Joon Sung Lee, for their supports, encouragements, and invaluable inputs for the current dissertation.
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PROFESSIONAL SPORTS SYNDICATES AND FAN DEMAND: THE SINGLE-ENTITY CASE OF MAJOR LEAGUE SOCCER

By

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August 2018

Chair: Brian M. Mills
Major: Health and Human Performance

The purpose of this work is to investigate the underlying implications of the Major League Soccer (MLS) organizational structure and understand and identify determinants of fan demand. As with the most U.S. major leagues, MLS has used cross-subsidization devices purportedly put in place to retain competitive balance, assumed to be demanded by fans and used as a legal defense from antitrust intervention. In addition, by directly sharing talent costs across teams, MLS differentiates itself from traditional cartel league structures. However, if competitive balance is not central to fan interest, the legal defense of league policies purportedly promoting league balance loses ground. Further, understanding the welfare effects of these policies on both fans and labor are pivotal to determining the net impact of this league structure on other stakeholders. Therefore, I investigate the determinants of MLS attendance and viewership demand with particular interest in relative and absolute quality, as well as the presence of the tradeoffs resulting from multiple consumption options. Within these studies, I find that attendees tend to avoid games with uncertainty over the expected outcome, while television viewers of these games were largely agnostic to uncertainty or balance. The absolute quality of the match, which includes both the home and away team quality, was found to increase attendance, while only home team performance quality was positively associated with television ratings. Superstar
effects were also present for both types of demand, with viewership demand responding only to the presence of superstars on the opposing team. Additionally, there were apparent substitution effects between television viewership and game attendance. Following the empirical investigation of fan demand, I derive economic implications of the current single-entity structure of MLS as an extension of past theoretical models of cartel and syndicate sports organizations. In this section, different implications of talent investment incentives are found based on various conjectural variations. In the last chapter, I conclude with summary of findings and general discussion and suggestions for future strategy and league policy for MLS as well as future studies.
CHAPTER 1
REVENUE SHARING AND TALENT SUPPLY CONJECTURE IN PRO SPORTS

Introduction

Antitrust law in the U.S. – the Sherman Act (1890), Clayton Act (1914), and Federal Trade Commission Act (1914) – aims to protect consumer wellbeing by ensuring fairness in competition among firms in a market. Specifically, these regulations forbid collusive behavior or formation of business cartels and discourage the emergence of monopolies. Nonetheless, professional sports leagues and franchises in the U.S. have thus far circumvented many of these regulations in pursuit of greater league welfare. Although only Major League Baseball was lawfully exempted from antitrust regulations in the 1920s, other major leagues – the National Football League (NFL), National Basketball Association (NBA), and National Hockey League (NHL) – have also enjoyed relatively favorable treatment from antitrust authorities. Therefore, professional sports leagues in the U.S. are generally regarded as business cartels, with structural features that allow cooperation between different teams, although the essence of a sports league is the sale of competition itself (Fort & Quirk, 1995).

Organizing as a business cartel can be effective in controlling the supply and price of a product in which cartel members hold stakes. Cartels are generally comprised of individual and independent firms that form collective agreements to inhibit competition and promote joint profits within the industry. Professional sports leagues in particular put great effort in fostering balance amongst their member teams to prevent anyone falling behind the others. As it is depicted in Neal’s (1964) Louis-Schmelling paradox where domination by a single champion would result in a loss of fan interest, or a general an unequal distribution of competitiveness across teams may eventually hurt aggregate profits for the league. Earlier, Rottenberg (1956) emphasized that fans are likely to value uncertainty in the outcome of the game, now known as
the Uncertainty of Outcome Hypothesis (UOH). This hypothesis has been driving much of the sports economics literature regarding demand for sport. The implication is that a concentration of high performing players in large markets could eventually deteriorate uncertainty and decrease overall fan interest, resulting in league collapse. It is therefore competitive balance that is purportedly the fundamental characteristic of the economic success of professional sports leagues, and thus used as a central defense for favorable antitrust treatment (Zimbalist, 2003).

Principal issues identified that degrade the level of competitive balance include the disproportionate distribution of resources amongst teams due to geographic restrictions and heterogeneous drawing potential, general financial viability, and the availability of substitutes. In this sense, major leagues in the U.S. have employed policies that are purported to equalize the distribution of resources amongst their member teams. Professional sports leagues in the U.S. therefore have been defending collusive behavior of their teams in the court by claiming that competitive balance would be harmed without revenue redistribution and restriction of player movement. Nevertheless, Rottenberg (1956; 2000) noted that league policies to control the distribution of talent will not affect competitive balance, an idea later coined Rottenberg’s Invariance Principle (IP). A substantial body of literature since the time of Rottenberg has tested the IP within professional sports to identify the effects of various league rules on competitive balance. However, although there exists work contradicting evidence about the usefulness of revenue sharing and other league policy mechanisms in impacting competitive balance (Késenne, 1996, 2000, 2004; Marburger, 1997), much of literature has found evidence supporting Rottenberg’s IP for league policies such as revenue sharing, the reserve clause, and salary caps, undermining professional sports leagues’ arguments for allowing collusive economic behavior (El-Hodiri & Quirk, 1971; Fort & Quirk, 1995; Vrooman, 1995).
In particular, Major League Soccer (MLS) adopted a single-entity structure upon its founding, purportedly to ensure greater financial stability and a more even distribution of team competitiveness (Francis & Zheng, 2010; Twomey & Monks, 2011). This structure is unique in that the entire league is treated as a single firm with many characteristics usually seen within business syndicates; however, most other U.S. professional sports leagues operate closer to a business cartel structure, treating its member teams as individual firms (Fort & Quirk, 1995). Specifically, MLS centrally controls all player contracts, national broadcasting contracts, and sponsorship sales, while paying dividends back to team owners and investors whenever MLS generates profits. Team operation is thus allocated to investors, who share a proportion of gate revenue with the league and keep any profits generated through local broadcasting and sponsorship deals. However, many economists have displayed skepticism over the need for explicit syndication of a professional sports league (Fort & Quirk, 1995; Késenne, 2015; Zimbalist, 2002). For example, Késenne (2015) noted problems that could arise from this structure, such as a reduced incentive for teams to invest in talent, suppressing player salaries, and leaving consumers with low quality teams. That is, in spite of possibly facilitating achievement of the league-wide balance, the product itself would be of inferior quality while greatly restricting costs for syndicate members.

From the empirical perspective, it is not clear whether MLS has generated a superior level of competitive balance through its current organizational structure. If the claim of ownership is to be believed, MLS should have relatively small deviations in win percentages across the league. Furthermore, the competitive balance defense of league cooperation implicitly assumes that fans cherish uncertainty over other factors, such as the absolute quality of the players or teams, and that this ultimate goal will make fans best off. However, Rottenberg’s
UOH requires substantial evidence, and the literature both within and across leagues has been mixed. Fort (2017) clearly notes that a league’s argument to employ mechanisms to improve balance tend to be faulty or weak at best, and that the UOH itself is only a hypothesis of fan preference that has been theoretically and empirically challenged over the years. Hence, there is a need for additional empirical work to justify the purported tradeoff between league, fan, and player welfare, and policies that claim to improve competitive balance. Closer scrutiny with respect to the effect of competitive balance or uncertainty of outcome on sports demand in various contexts and league structures is therefore necessary. I seek to fill this gap through both theoretical modeling of the structure of MLS and empirical evaluation of fan demand for the league.

In this context, further investigation of the economic design specific to the professional sport syndicate structure should be carefully modeled to understand the underlying implications of largely shared talent costs. The difference in talent distribution mechanisms and revenue (cost) sharing may yield different effects on league and team decisions and fan behavior compared to that of the more common cartel structure. Additionally, many previous models implicitly assume that fans prefer competitive balance and outcome uncertainty, which then affects the revenue function of the league and teams. However, more recent empirical studies have found that fans in some leagues tend to favor individual superstars over equality in team strength, in some cases showing preferences for more certain game outcomes (Buraimo & Simmons, 2008; Buraimo & Simmons, 2015; Coates & Humphreys, 2010; Coates, Humphreys, & Zhou, 2014; Beckman, Cai, Esrock, & Lemke, 2011; Mills, Salaga, & Tainsky, 2016; Tainsky & Jasielec, 2014). Therefore, further examination is needed to unravel the desirability of competitive balance and outcome uncertainty in a relation to demand for syndicate sports leagues and MLS in particular.
Purpose of the Study

As stated earlier, the purpose of the current paper is to understand and identify determinants of demand for MLS and to investigate economic implications of the syndicate league structure of MLS. I first review the sports league modeling literature and assess the implications of resource-redistributive policies, particularly with respect to effects on competitive balance and talent investment in the following section. As noted earlier, despite Rottenberg’s UOH spurring much research into its effect on demand, no consensus has been made as to the influence of tightly matched (uncertain) games on fan interest and fan welfare. Relatedly, recent work from Coates, Humphreys, and Zhou (2014) has suggested guidance on why empirical research has reached mixed results when modeling sports demand and UOH, and I use these lesson to guide my inquiry. I first empirically investigate the determinants of MLS attendance demand with particular interest in relative and absolute quality. In this study, I found evidence of an opposite relationship to that predicted by UOH: fans of MLS preferred games that had greater certainty in expected game outcome, while there was a preference for teams with better performance and more superstars. These results provide evidence for the behavioral theories in which consumer choices are determined by the relative loss or gain of enjoyment derived from each game, avoiding games with uncertainty over the expected result. As an extension to the attendance demand study, I examine determinants for local market television viewership for MLS in Chapter 3. I find that uncertainty of outcome has no explanatory power for television viewership, while the presence of superstars for opposing teams and the performance quality of the local team were associated with an increase in ratings. Further, there was evidence of substitution between attendance and viewership: weather and seasonal effects were similar in magnitude and in the opposite direction found in the attendance study, while excessive demand beyond stadium capacity is captured through television viewership even after
controlling for various game and team quality measures. These implications raise questions about the single-entity status of the league, with defenses often centered upon instituting competitive balance to enhance fan welfare. In Chapter 4, I discuss the distinctive features of the MLS league structure, and identify a gap that exists within the literature on modeling the syndicate league. As the majority of work modeling sports leagues takes place in the traditional cartel structure, some underlying assumptions may not yield the same results in the syndicate structure. These models consider talent investment effects that result from the single-entity structure. The result is compared with traditional cartel leagues as a new contribution to the literature on sports league modeling. Additionally, various conjectures on talent investment is introduced to derive structural implications in a two team league case. I find that the optimal level of talent will be higher in syndicate league whenever acquisition of talent of a team results in any type of loss for the other team while it will be reversed whenever the acquisition of talent by one team results in any type of compensation in talent for other teams. Finally, I provide ultimate conclusions from this work and suggest directions for future inquiry in Chapter 5.

Competitive Balance and the Economics of League Design

Over a half century ago, Rottenberg (1956) posited that unpredictability in the outcome of sporting contest is an essential element in retention of fan interest. That is, domination of a team or a player in competition can hurt the attractiveness of an individual sporting contest or league. Specifically, high volatility in the race for a championship is proposed as a primary driver of fans to the stadium (Neale, 1964). In this sense, most major leagues in the U.S. have employed policies that are argued to improve competitive imbalance that exists across teams with varying drawing power. Although there exist antitrust laws that prohibit collusion between firms, Major League Baseball is exempt from antitrust law, and other leagues have thus far been treated quite favorably in the application of antitrust law. The core argument of such policies is
that even distribution of on-field competitiveness within the league is vital to its survival so that concentration of resources to teams in more lucrative markets enables them to hire superior playing talent that affects success on field. In turn, the performance and competitive balance of teams within the league will be disproportionately distributed toward teams with greater resources (Neale, 1964; Rottenberg, 1956; Szymanski, 2003). Teams with fewer resources in these leagues are left out of the market for top talent, reducing outcome uncertainty, fan interest, and ultimately, aggregate league revenues.

Nevertheless, Rottenberg (1956; 2000) stated that leagues’ effort in controlling the mobility of playing talent would not result in the convergence toward an equal distribution of player talent amongst teams regardless of resource redistributive policies, since players will end up where they are mostly valued. This is the essence of IP that has driven much of sports economic literature. Specifically, subsequent work has shown that teams will eventually sell their playing talent until they reach a revenue maximization point – that is, the marginal revenue product of talent for a large-market team will be equal to the marginal revenue product of a small-market team – resulting in no change to the distribution of talent in the face of league interventions purported to do so (Fort & Quirk 1995; Vrooman, 1995). Within this context, a common league labor policy, the reserve clause, has been discussed extensively upon the arrival of free agency. The reserve clause of MLB, which was abolished in 1975, enabled each team to hold the absolute contractual power over each players, with this power renewable yearly at the team’s sole discretion. That is, players had no negotiating power over their contract once signed, stripping much of their ability to increase their salaries as would be expected in a competitive labor market. The core argument of this policy was again to prevent skewed distribution of playing talent to rich teams. Nonetheless, empirical work has tested changes within MLB,
finding no evidence of competitive balance effects upon the arrival of free agency or introduction of the draft system (Lee & Fort, 2005). In terms of player cost, Fort and Quirk (1995) noted that the equilibrium cost of players under the reserve clause is lower than in the free agency. These findings imply that while competitive balance is unaffected under free agency, wealth is simply reallocated from players to the owners through playing talent rights retained by the team in perpetuity. That is, the effort to control player movement was rather effective in depressing player salary, but did little in creating a more balanced league. Team owners are appropriating the rent generated by players through holding their property rights, transferring wealth from players to team owners. For instance, Scully (1974) empirically demonstrated the exploitation of players by team owners in MLB under the reserve clause, finding that average players were receiving approximately 11 percent of their marginal revenue product, while ‘superstar’ players received only about 15 percent of their value.

Given that competitive balance is purported to be key to interest in sporting contests, policies of major leagues to adjust competitiveness amongst its member teams has been the essence of their antitrust argument to allow policies that reduced player salaries. El-Hodiri and Quirk (1971) were one of the first to address professional sports league design. They recognized outcome uncertainty as a fundamental element for economic success of sports teams as it relates to the gate attendance, following from Rottenberg (1956) and Neale (1964). Their model assumes that every team within the league would avoid becoming extremely dominating as noted by the Louis-Schmelling paradox (Neale, 1964), while home attendance is an increasing function of winning. That is, the revenue of each team is a concave function of probability of winning, where the maximum can be found at some point beyond 0.5 but less than 1. Empirically, it was found that fans rather prefer to see their home team winning, while attendance was maximized.
when the probability of home team win was between 0.6 and 0.7 (Knowles, Sherony, & Haupert, 1992; Rascher, 1999). Additionally, Coates and Humphreys (2010) find similar results in the NFL, where fans tend to prefer games where the home team is expected to win with a larger score margin, avoiding closely matched games in which the home team is expected to lose. Therefore, the revenue function is concave: as marginal revenue decreases as win percentage increases. This means that each team has an economic incentive to become slightly better than others, while avoid becoming completely dominant. The league model of El-Hodiri and Quirk (1971) has since significantly influenced the development of various subsequent models of sports league design.

Further, a more exhaustive overview regarding U.S. pro sports league design and league policies was covered by Fort and Quirk (1995). The authors identified a central issue in the structure of professional sports leagues, cross-subsidization, presumed to be essential for the overall success and survival of a league. Without the subsidization, it is argued, teams in small markets (i.e., weak-drawing cities) would not have sufficient incentives to elevate their competitiveness to that the level of a large market (i.e., strong-drawing cities), inhibiting the maximization of total revenue or profits generated within the league. In the absence of any form of subsidization for the smaller market team, competitive balance could be reduced, in turn reducing joint-profitability of all teams. However, Fort and Quirk (1995) examined the effects of cross-subsidizing league policies and found that these have little effect on the incentive for owners to make investments in ways consistent with improving balance. The base assumption of their model is that team owners and players maximize their wealth (e.g., profit), now a common assumption for U.S. leagues. The magnitude of revenue for each team is then dependent on market size and win percentage, which affects the stream of revenue from both gate receipts and
local television contracts. Ultimately, the market outcome converges toward an equilibrium point at which marginal revenue with respect to added performance (win percentage) of the large and small market team intersects.

Among many cross-subsidization policies employed by professional sports leagues, revenue sharing has received the most extensive attention in the league modeling literature. The most commonly studied revenue sharing types include gate revenue sharing, pooled revenue sharing, and media revenue sharing. Teams share a certain proportion of home gate receipts with visiting teams under gate revenue sharing, while teams share a certain proportion of revenue equally amongst its member teams in pooled sharing. Media revenue can be divided into national and local broadcasting revenue, while only sales of national broadcasting rights are shared in most cases. Fort and Quirk (1995) posited that gate revenue sharing will lower the value of additional win percentage while unshared local television contracts may worsen the value of winning. They show that the equilibrium of marginal revenue point in a two-team league will be unchanged even under the gate revenue sharing so that competitive balance is unaffected. The equilibrium result, however, reveals that gate revenue sharing lowers the value of playing talent since each team can only appropriate a small fraction of increased revenue from additional winning. Furthermore, they find that gate revenue sharing and national broadcasting revenue sharing does not affect the changes in competitive balance as intended.

Alternatively, assuming revenue from local broadcasting sales is dependent on the drawing potential of a team, keeping these revenues will create a disproportionate revenue distribution between teams in different cities, and therefore deteriorating the league balance. In sum, both El-Hodiri and Quirk (1971) and Fort and Quirk (1995) found that the majority of league policies that redistribute member franchise resources, or restrict labor movement (i.e., the
reserve clause, amateur draft, territorial rights, exclusive local media contracts, and revenue sharing) do not affect competitive balance, exhibiting theoretical and empirical evidence to support Rottenberg’s IP.

However, the IP is not supported by all economic models of all sports league collaborative or redistributive policies. Although prior work showed that gate revenue sharing would not change the level of competitive balance (Fort & Quirk, 1995; Vrooman, 1995), Marburger (1997) claimed that greater sharing of gate revenue would enhance competitive balance. His modeling followed the previous assumption that attendance is an increasing function of the relative quality of both competing teams. However, he also added the importance of absolute quality of each team so that fans would prefer quality home and visiting team although preference for home team quality outweighs the visiting team quality. Additionally, he made an alternative assumption such that player acquisition of one team would have no negative externality for other teams. In particular, Marburger argues that talent acquisition is not zero-sum in leagues with more than two teams, as suggested in previous work (El-Hodiri & Quirk, 1971; Fort & Quirk, 1995). With these assumptions, he argued that there will be greater incentives for weaker teams to invest in more playing talent since revenue sharing reduces the marginal revenue product for the large market more than the small market team. Therefore, competitive balance would be improved.

Although Marburger (1997) did not expand upon models with non-zero-sum game of talent acquisition assumption, this may be in line with a more recent stream of debates on the different implications for revenue sharing and its effect on competitive balance. Major leagues in the U.S. are traditionally considered as fixed talent market where no other competing league is present domestically and even internationally. The fixed (inelastic) labor market refers to a
supply of talent that is limited such that talent acquisition by one team comes at the cost of another. In other words, talent transfers are fully zero-sum. In an open (elastic) labor market, on the other hand, the supply of talent is treated as unlimited for a given league, where player acquisition by one team is generally independent from other teams in the league. In general, European sports leagues are considered to have open labor market where talent supplies are relatively unlimited due to the larger talent market internationally.

In this context, the work of Szymanski (2004) and Szymanski and Késenne (2004) question previous modeling assumptions of El-Hodiri and Quirk (1971) and Fort and Quirk (1995). In particular, they note that these models have assumed talent choices based on joint-profit maximization for the league, or a cooperative game, while the authors argue teams’ talent choices are in fact independent of one another, making talent choice a non-cooperative game following Nash equilibrium. In this case, a gain in talent for one team does not necessarily mean a loss for the other team, a non-zero-sum game. In other words, acquisition of talent for one team does not leave other teams with direct loss of talent since teams are not bound with single choice as it was assumed in previous fixed supply of talent for the league. Within the two team model, this indicates that a marginal talent increase for Team 1 results in zero effect on the talent choice of (availability for) Team 2 and vice versa, while prior models assumed this to be a unit loss for Team 1. They define this as Nash conjecture, with previous models were characterized under Walrasian conjectures. Under the Contest-Nash equilibrium, the IP no longer holds for a gate revenue sharing scheme (El-Hodiri & Quirk, 1971; Fort & Quirk, 1995; Vrooman, 1995). Instead, Szymanski (2004) and Szymanski and Késenne (2004) found deteriorations in competitive balance under revenue sharing under the Nash conjecture setup.
However, Winfree and Fort (2012) argued that the presence of these differences can be resolved by including a talent investment dimension to the classical model. This alteration integrated the Nash conjecture for both fixed and open leagues to reach equilibrium, and exhibited the IP more generally. Yet, Szymanski (2013) rebutted this argument by noting that talent investment was already included in a previous model such that IP could not survive despite the added investment dimension. He shows that IP would hold only if the marginal revenue function is identical between teams where the league is perfectly balanced.

Szymanski (2013) also notes that Madden (2011) introduced a differentiated modeling approach where the market power of teams was integrated into the model through game theoretic methods, term the strategic market game (SMG). That is, he posited that expenditure on talent is a strategic choice of each team, and in which the revenue function includes both relative and absolute quality. He argue that SMG approach incorporates strategic interactions between team choices and that Nash approach is a special case of SMG approach where talent supply is perfectly elastic; however, he argues that the Walrasian approach does not incorporate any strategic interaction between teams. Furthermore, Madden (2013) provided additional response to the discussion between Szymanski (2013) and Winfree and Fort (2012; 2013), noting that the Walrasian conjecture and the IP cannot be retained when talent investment is the strategic variable. But Winfree and Fort (2013) note that their effort was to drive existing literature toward a more inclusive modeling direction that covers various assumptions and reduces confusion on the dimensional differences between talent level and talent investment. Additionally, Winfree (2015) disagreed with Madden’s (2011; 2013) arguments on generalizability of the model and assumptions made on his work. Rather, he argued that the definition of talent is nebulous, and winning (or the success of a team) is not explained solely by talent level or investment (Winfree
& Fort, 2012). Furthermore, prior work had already included variations in talent supply elasticity. Hence, it is contended that Madden’s (2011; 2013) model lacks the necessary conditions for the IP to hold, and *Nash* conjectures do not necessarily converge into his model. Ultimately, Winfree (2015) notes that discussion of conjectural difference should be continued, and there exists a need for further development of league modeling with conjectures specific to the conditions under which each league operates.

Despite the extensive discussion on league modeling and its assumptions regarding traditional cartel sports leagues, there remains limited investigation into syndicate leagues. Vrooman (1997) proposed that syndicate owners who share risk with other partners will have more incentive to invest in talent, while player salary would be much greater than in profit driven cartel leagues. However, past work has shown that this has not been the case in MLS, where player salary has been significantly suppressed (Twomey & Monks, 2011). Most relevant to MLS and its syndicate design, Easton and Rockerbie (2005) investigate various implications of traditional and centrally pooled revenue sharing with different talent supply conjectures, including the MLS case. They lay out three different conjectures: (1) Cournot conjectures as no impact of one team hiring talent on others that is similar to *Nash* conjectures, (2) competitive conjectures as one team hiring talent resulting in loss for others that is similar to *Walrasian* conjectures, and (3) cartel conjectures such that, in order to maintain market share, every team increases their own stock of talent if any one team increases theirs which they argue to be a case for MLS. The cartel conjecture is then a case where player distribution is centrally controlled through the league and each team receives an equivalent share of talent in order to maintain each team’s market share. They found, under the cartel conjecture, centrally pooled revenue sharing will incentivize existing teams to increase the overall pool by allowing more expansion members.
only if new team has average revenue above the league average. However, Chang and Sanders (2009) show that this is not a case for a cartel league, where increased pooled revenue sharing lowers player investment incentives under more traditional assumptions with fixed talent supply. Unlike previous literature on gate revenue sharing, they find that pooled revenue sharing will eventually worsen competitive balance since there is disincentive for investing in playing talent for each team due to lower revenue teams not reinvesting shared revenue back into talent. The authors also suggested the possibility of equivalent effects if market size differences increase.

Lastly, Késenne (2015) posited that the single-entity league creates monopsonistic market power on players by the league being the sole buyer in the market. Compared to competitive labor market, he shows that fewer players will be hired with salaries below marginal revenue, exploiting its players under profit maximizing league. On the contrary, if the league’s objective it to maximize its overall quality, the league overcompensates its playing talent under breakeven constraint which can be seen where labor market is more competitive. He also shows that the single-entity league will have higher ticket prices compared to the optimal fan welfare level due to increased market power from local monopolies created through the absence of team relegation (i.e., closed league). Additionally, he notes that collective sales of media rights create excessive monopoly in the media market, leaving consumers with higher prices and fewer televised games. In contrast to Easton and Rockerbie (2005), Késenne (2015) argues that this type of league will have a sub-optimal league size with respect to aggregate welfare of the league, players, and fans, as the number of teams will be limited to protect the share of inside member teams.

Despite varying implications for the single-entity league (Easton & Rockerbie, 2005; Késenne, 2015), MLS has witnessed a significant increase in fan interest and has been expanding
aggressively within the last decade. In this context, there is a need for investigation of demand in a syndicate professional league to more clearly understand the implications of organizing as owner-investors, rather than independent owners.

Both cartelization and syndication of professional sports aims to protect the economic wellbeing of insider teams (or investors). In order to protect the aggregate profits of all teams, domination of a few teams over others within the league is then greatly restrained. This restriction, however, would be stronger in a syndicate league since league-wide decisions are made centrally through collective agreements by its member teams to reduce financial risks. For instance, the major reason of NASL’s failure was the exacerbated arms race between teams, which forced less resourceful teams to exit the league, eventually leading the league to cease its business. Hence, under the syndicate league, player investment at the individual team level will be highly limited to ensure the prevention of league domination by a small group of teams, which may lead to financial failure at the league level.

MLS, as a successor of NASL, therefore initiated the league with a goal to prevent this by adopting the single-entity structure, where revenue and talent allocation are centrally shared and controlled. As syndicates of professional sports leagues have strong motives to ensure financial stability through balanced growth of their teams, MLS may also be putting greater weight on promoting league balance rather than improving its quality. That is, the implicit ultimate objective of MLS is then to promote competitive balance amongst member teams while suppressing playing talent investment. Nonetheless, this goal only accounts for welfare of the team owners or investors, neglecting the fan or player welfare. If quality players are prevented from entering the league due to restrictions on roster size or suppressed salaries, affecting the overall quality of the league, fans may eventually lose interest. Also, if fans do not prefer a
balanced league, syndication of professional sports could hurt future profits in spite of the appeal of short term financial stability.

In this context, I investigate the determinants of demand empirically to identify where MLS fans’ preferences are placed. If MLS fans are not particularly interested in well-balanced matches, and if they prefer greater absolute quality, it may be time for MLS to reconsider its state of business to accommodate the needs of its consumers. Furthermore, I delve into the theoretical structural design of MLS to derive further implications for the league policy and its operation in regards to talent investment.
CHAPTER 2
ESTIMATION OF GAME-LEVEL ATTENDANCE IN MAJOR LEAGUE SOCCER: OUTCOME UNCERTAINTY AND ABSOLUTE QUALITY CONSIDERATIONS

Introduction

Soccer is perhaps the most popular sport internationally, both at the amateur and professional levels. Professional soccer in the United States, however, has thus far not experienced nearly the success of its counterparts in Europe. The historical lack of success of the sport reached a peak with the failure of the North American Soccer League (NASL) in the mid-1980s. However, this failed league was replaced with Major League Soccer (MLS) in 1996, which has grown considerably, particularly since 2004. Despite this growth, there has been skepticism about whether a professional soccer league can survive as an equivalently major league sport within the U.S. setting that includes incumbents such as the National Football League (NFL), Major League Baseball (MLB), the National Hockey League (NHL), and the National Basketball Association (NBA; Mendelsohn, 2003).

Nevertheless, as both the men’s and women’s U.S. national soccer teams increase their international competitiveness, a burgeoning interest in the sport within the U.S. has seemingly followed. In 2014, an estimated 26.5 million U.S. soccer fans watched the men’s World Cup Final (Stubits, 2014), a game that did not even feature the country’s own team, while an estimated 23 million people tuned into the 2015 women’s World Cup Final. MLS has also been slowly exerting greater influence on sports fans throughout the continent by expanding its reach to new markets like Orlando, Florida. Moreover, average attendance for MLS games in the 2015 season was recorded at 21,546 (Soccer Stadium Digest, 2015), nearly 4,000 more than the average game attendance in both the NBA (17,809) and in the NHL (17,503). However, the level of interest has yet to meet game attendance levels seen in other major leagues such as the NFL (68,776) and MLB (30,346). The increase in interest, therefore, brings forth relevant questions
regarding the determinants of this growth, and how the league can foster continued future increases in fan interest.

MLS has received some academic attention due to its peculiar single-entity organizational structure (Francis & Zheng, 2010; Jakobsze, 2010; Mendelsohn, 2003). This centralized league control over the distribution of talent is specifically intended to reduce liabilities of the investors (Jakobsze, 2010) while also suppressing player salaries and (supposedly) improve balance between teams (Mendelsohn, 2003). The centralized control over talent raises the question of how soccer may optimize the distribution of talent across the league to ensure increased demand among fans. As the league’s effort is centered in balancing the competitiveness of teams within the league and/or placing players with the highest values in the largest markets, there is a question as to whether the league would be best served focusing on balance – as predicted by Rottenberg’s Uncertainty of Outcome Hypothesis (UOH) – or on improving absolute quality through creating superstar teams that attract fans when playing both home and away.

In particular, there is a lack of extended dialogue related to the role of UOH in MLS fan interest, though recent work has begun to address some of these questions (Shapiro, DeSchriver, & Rascher, 2017). Paul and Weinbach (2013) have directly estimated the relationship between uncertainty and MLS demand, confirming its predictions. However, their study was set in the context of broadcast viewership. As noted in Mongeon and Winfree (2012), demand for attendance may be determined differently than for television. This may be particularly relevant in the face of recent evidence from Coates, Humphreys, and Zhou (2014) related to the role of uncertainty on consumers’ choices to attend games, which have a larger cost commitment than viewing on television. Alternatively, Jewell (2017) finds limited evidence of a relationship
between uncertainty and MLS attendance in the direction predicted by UOH. This work uses the absolute points per game difference between the two competing teams. However, this measure is not a direct measure of match uncertainty, but relative team quality, and the purpose of the central model was to test marquee player influences, rather than evaluate UOH itself. Further, the measure was susceptible to more fluctuation early in the season that could obscure regression estimates, a problem described in McDonald and Rascher (2000).

More robust empirical evidence is therefore needed to establish any relationship between uncertainty and MLS attendance demand to guide further managerial or policy prescriptions for league development. Hence, this work investigates the determinants of demand by separating UOH-related variables with absolute quality related variables in the context of attendance demand. I estimate game-level attendance as a function of betting lines converted into home team win probability to identify the impact of uncertainty while controlling for absolute quality through Elo ratings – a dynamic measure of team strength – and superstar effects using DP indicators and salaries. The current estimation results reveal a convex relationship between home win probability and attendance, consistent with the predictions of Coates et al. (2014). Specifically, high quality home or away teams are important to fans, while attendance is minimized when there is substantial uncertainty over the outcome of the game.

Background and Literature Review

The Landscape of U.S. Professional Soccer

In the 1970s the U.S. had apparently witnessed a peak of interest in professional soccer with presence of NASL. The signing of world class athletes, such as Pele from Brazil, generated great interest in soccer in North America (Francis & Zheng, 2010). The New York Cosmos, the biggest club in the NASL at the time, had enjoyed an average of 40,000 fans per game after acquiring many star players. Nevertheless, not all teams in the NASL could keep up with the
financial burdens associated with signing superstar players, and eventually ceased it operations, folding in 1984 after continuous attendance decline. After 12 years without a major professional soccer league in the U.S., MLS launched in 1996 as part of an agreement made to host 1994 World Cup.

As the successor to the NASL, MLS structured itself in a way to prevent similar failures of operation that resulted in the shuttering of its predecessor’s (Francis & Zheng, 2010). The major obstacle for the MLS to achieve any success was to attract star athletes while suppressing the associated costs (Mendelsohn, 2003). To overcome these hurdles, MLS adopted a single-entity league structure to ensure the stability of the new league and to lure potential investors with reduced financial risks (Francis & Zheng, 2010; Twomey & Monks, 2011). The single-entity structure allowed centralized control of the distribution of talent around the league, presumably reducing the likelihood of dominance of a single team at the expense of many other teams that could not afford top flight talent. Yet, in order to attract investors and offer stronger incentives to be a part of the league, MLS enabled its stakeholders to gain control of a team and oversee daily operations, where each owner was responsible for employment of staff while receiving half of the revenue generated by ticket sales and concessions (Jakobsze, 2010).

Nonetheless, the single-entity structure did little to reduce league dominance of a single team early on, as D.C. United appeared in the league’s championship game in each of the first four seasons of MLS operation, winning three times.

Furthermore, this single-entity structure facilitated monopsony power of the league, given that player contracts have largely been determined centrally, rather than by individual teams. Therefore, MLS has thus far effectively suppressed player salaries. For example, Twomey and Monks (2011) found that spending on player salaries in MLS made up only about 25 percent of
revenues, while other major leagues in the U.S. spend between 40 and 60 percent. However, in recognizing the value of superstar effects (Berri & Schmidt, 2006; Hausman & Leonard, 1997; Lucifora & Simmons, 2003; Rosen, 1981), MLS made a notable exception to its salary rules when it allowed the L.A. Galaxy to sign David Beckham – one of the most well-known professional soccer players at the time – to an unprecedented 5-year, $32.5 million contract in an effort to increase league awareness and popularity (Francis & Zheng, 2010; Lawson, Sheehan, & Stephenson, 2008). This type of signing later became part of MLS policy – known as the DP Rule – allowing for up to three roster spots with salaries that exceed the league cap. As a result of this policy, MLS has successfully attracted some high performing global stars as the league continues to grow, and these stars have been shown to attract additional fans both when playing at home and on the road (Jewell, 2017; Shapiro, Deschriver, & Rascher, 2017). However, while past work has focused on these superstar effects, there has been very little focus on the influence of uncertainty of outcome and absolute quality on attendance, a central area of focus in demand study in sport management and sports economics. In this work, I therefore expand upon past findings with respect to uncertainty of outcome using more novel measures of quality and uncertainty at the individual game level.

**Determinants of Sports demand**

**Outcome uncertainty**

The demand for sport has been a central area of research within sports economics, with important implications related to policy determination, evaluation of league and franchise monopsony and monopoly, and ticket sales in professional sport (Rottenberg, 1956; Neale, 1964; Scully, 1974; Meehan, Nelson, & Richardson, 2007; Soebbing, 2008; Borland & MacDonald, 2003). The first full specification of demand for sports attendance was described in Rottenberg
(1956) as including various determinants such as market size, income, team quality, goodness and availability of substitutes, and uncertainty over the outcome of the contest.

The bulk of research on demand for sporting contests has been entrenched in Rottenberg’s (1956) uncertainty of outcome hypothesis (UOH), given its various implications for league policy and favorable antitrust treatment of leagues. In particular, the uncertainty of outcome hypothesis makes the claim that fans tend to prefer uncertain game or season outcomes to known ones. This proposition has guided many pro sports league policies – or at least provided a pretext for their use\(^1\) – such as salary caps, revenue sharing, “luxury taxes”, and the reverse order draft. Specifically, if fans benefit from more balance, then it follows that policies to spread the distribution of playing talent across more teams would result in more interest.

There are various types of outcome uncertainty discussed in the economics literature: (1) game or match uncertainty, (2) playoff or championship uncertainty, and (3) consecutive season uncertainty (Cairns, 1987; Sloane, 1976; Cairns, Jennett, & Sloane, 1986; Lee & Fort, 2008; Mills & Fort, 2014; Szymanski 2003). Game or match uncertainty refers to the outcome of a single match. Playoff or championship uncertainty is characterized as the variation in expectations for a given team to make a playoff or win a league championship. Consecutive season uncertainty refers to the tendency for the same team(s) to win from season to season (dynasties).

Specifically, in terms of game or match uncertainty, the predictions imply that while home fans will increase their likelihood of attendance as their local team increases in quality, there exists an inflection point at which uncertainty decreases to a level that would also decrease

\(^1\)We leave for another time the discussion of Rottenberg’s Invariance Principle relating to the effectiveness (or lack thereof) of these policies in redistributing talent around the league and improving balance and uncertainty.
attendance, despite a sure win from the home team. This results in an inverse U-shaped relationship between home team’s winning probability and attendance. Various empirical work has, indeed, found evidence consistent with UOH’s predicted inverted U-shaped relationship between home win probability and attendance (Knowles, Sherony, & Haupert, 1992; Rascher, 1999; Rascher & Solmes, 2007). Yet, despite the UOH being in the center of discussion, much of the empirical research has produced inconsistent results regarding the predictions of the UOH (Szymanski, 2003). More recent work has found a U-shaped relationship, in which greater certainty about the outcome is associated with larger attendance levels or total spending on a given game (Buraimo & Simmons, 2008; Beckman, Cai, Esrock, & Lemke, 2011; Coates & Humphreys, 2010; Czarnitzki & Stadtmann, 2002; Lemke, Leonard, Tlhokwane, 2010; Mills, Salaga, & Tainsky, 2016).

As with much of the sports demand literature, UOH has played a central role in the theoretical contributions to understanding league policies as it relates to demand estimation in professional soccer. Like much of the literature on demand in other sports, evidence for the UOH in soccer is rather mixed. Many studies in soccer have focused on match uncertainty, often in the international context, using betting information as a proxy of outcome probability. Benz, Brandes, and Franck (2009) find that Bundesliga attendance is positively related to improvements in outcome uncertainty using data from the 2001 through 2004 seasons. In contrast, Peel and Thomas (1992) found that English fans preferred more certain home team wins across four different English divisions, with similar evidence coming various related work (Buraimo & Simmons, 2008; Forrest & Simmons, 2002; Forrest, Beaumont, Goddard, & Simmons, 2005). While Coates et al. (2014) use this relationship as support for a home fan loss aversion hypothesis in the MLB context, the occurrence of a U-shaped relationship between
demand and uncertainty allows for various interpretations. For example, related work has noted that the measured behavior is also consistent with home fans having interest in a dominant division leader, a superstar visiting team, individual superstar players, or a general interest or support for underdogs (Buraimo & Simmons, 2002; McGinnis & Gentry, 2009; Mills, Salaga, & Tainsky, 2016 in MLB).

Nonetheless, majority of soccer-specific studies have been conducted within the European context, leaving soccer in the U.S. with room for further exploration. Specifically, the structure of MLS is vastly different from European soccer. Most saliently, MLS has no promotion or relegation system. In this case, the various competition levels and multiple level talent investment decision points in European leagues – such as overly heavy investment for promotion or to avoid relegation – could affect estimation and interpretation of uncertainty of outcome effects, particularly when extrapolated to U.S. leagues (Peeters & Szymanski, 2014). In the U.S. context, only Jewell (2017) includes a single measure of uncertainty within a demand or attendance estimation, finding no effect of uncertainty in the MLS context.

**Absolute Quality**

In understanding demand for sport many studies also consider absolute quality of both competing teams in addition to their relative quality (uncertainty). Specifically in literature on professional soccer, absolute quality is measured using the number of goals per game (Dewenter & Namini, 2013), total league points (Buraimo & Simmons, 2008; Czarnitzki & Stadtmann, 2002; DeSchriver, Rascher, & Shapiro, 2016; Jewell & Molina, 2005) or league standing (Benz, Brandes, & Franck, 2009; Czarnitzki & Stadtmann, 2002; Peel & Thomas, 1992), the payroll of each team (Buraimo & Simmons, 2008), or the number of star players (DeSchriver, 2007; Jewell, 2017; Lawson, Sheehan, & Stephenson 2008).
The work of Jewell and Molina (2005) was the first attempt to estimate the determinants of attendance for the MLS. Specifically, they tested ethnic components to fan interest, finding that the size of a local Hispanic population was in fact negatively associated with attendance. This finding was relevant to sport managers and marketers in particular, as MLS marketing was geared toward penetrating a Hispanic population that is normally considered to play a central role in soccer demand in the U.S. The authors also found evidence for substitution effects between MLS and the NFL, but reveal no effect of team quality on attendance using league points. Alternatively, DeSchriver, Rascher, and Shapiro (2016) found positive relationship between attendance and proportion of Hispanic population, though this was not central focus of the study. More importantly, they found novelty effect of expansion teams on attendance while finding no significant effect of soccer specific stadiums, identified as another supposed key growth strategy taken on by MLS. However, there was no direct test of Rottenberg’s UOH on either of these studies.

One of the most interesting peculiarities of MLS lies within its Designated Players (DP) rule, which has been addressed to some extent in recent literature. For example, DeSchriver (2007) and Lawson, Sheehan, and Stephenson (2008) find that the presence of DPs can greatly increase the attendance at both home and away games. Jewell (2017) finds similar results, but that these effects tend to diminish over time. Nonetheless, the introduction of the DP rule has created a problem of salary disparity within a team. For instance, the highest paid player running for New York City FC in 2015 season received base salary of $6,000,000, while lowest paid player received $50,000, less than 10 percent of the maximum salary (MLSplayers.org, 2016). While these salaries had the ability to attract star players, Coates, Frick, and Jewell (2016) revealed that greater inequality in salary distribution within a team due to the DP rule was
negatively associated with productivity in terms of league points. The authors note that this has constrained spending among some teams, perhaps resulting in a tradeoff between performance effects on fan interest and superstar effects known to wane over time (Jewell, 2017). Therefore, understanding the relative interest in each of these characteristics is particularly important for league organization and teams looking to maximize profits.

**Other Determinants**

While absolute and relative quality have played a central role in estimations of demand, given their importance in describing market power of franchises and leagues, most demand estimations include various other likely determinants of fan interest. Rivalry, for example, has become a focus in both managerial and economic inquiries into fans. Much of previous literature considering rivalry matches has found evidence of positive effects on both attendance (Beckman et al., 2011; Buraimo & Simmons, 2008; Forrest & Simmons, 2002; Forrest et al., 2004; Lemke et al., 2010; Paul, 2003) and viewership demand (Alavy, Gaskell, Leach, & Szymanski, 2010; Forrest, Simmons, & Buraimo, 2005; Sung, Mills, & Tainsky, 2017). However, the definition of rivalry in these studies varies. For example, most European professional soccer studies define rivalry with derby teams, while most of the studies in the U.S. major league studies define rivalry with divisional teams due to absence of geographical proximity. In terms of MLS research, only Jewell (2017) tested the effect of rivalry matches, finding a positive impact on attendance.

Traditionally, demand studies also include economic characteristics such as price, population, and income to account for attributes of each team or geographical area. In particular, Jewell and Molina (2005) and Lawson et al. (2008) previously included variables such as ethnic composition of the population, size of the population, and income in estimating the demand for the MLS. However, unavailability of game-level price data for most of the major leagues in the U.S. limits the understanding of the specific price effect on attendance.
Conceptual Model and Hypotheses

Although largely accepted as a likely driver of fan interest, Coates et al. (2014) note that there has been a limited effort in theorizing UOH, developing a new model based on reference-dependent preferences in an effort to improve our understanding of demand estimation in sport. Amongst their model specifications, they show a concave function, where expected utility is maximized when games are closely matched following Rottenberg’s UOH. On the other hand, the authors present an alternative model that is useful in understanding demand in terms of (utility) loss averse fans in particular. Loss averse fans will avoid consumption of games that are likely to offer lower utility than their expectation. These fans will attend games that home team is highly expected to win. The authors also speculate that fans will also attend games in which the home team is expected to lose, gaining high levels of utility from the prospect of an upset that outweighs the loss of utility for an expected loss. In this sense, the authors present a convex function – a right-side-up U-shape in contrast to the inverted U-shape predicted by UOH – where utility is maximized when the outcome of the game is more certain and minimized when the uncertainty is at its peak.

First, I define the following simplified general demand (attendance) function for the MLS.

\[ \text{Attendance} = f(P, EC, OU, HTQ, ATQ, HS, AS) \]

where the attendance of a match is explained by price (P) economic characteristics (EC), outcome uncertainty (OU), home team quality (HTQ), away team quality (ATQ), and the presence of home and away team superstars (HS and AS, respectively). However, I note that the
current empirical specification does not include price. Price data for individual teams and matches was unavailable, and I therefore note that I estimate determinants of attendance, rather than a full demand function. Further, it is unlikely that prices fluctuate from game to game or season to season substantially in this short panel, and the home fixed effects account for unobserved differences in prices across teams, while yearly fixed effects account for generalized price changes across years. Lastly, while I estimated models including population and income, the lack of variability across the data’s short time period shows little effect of these variables on attendance. This allows the specification to focus on the uncertainty and absolute quality-specific variables of central interest.

From this specification of the attendance function, I put forth the following hypotheses based on Coates et al. (2014):

**H1:** Home attendance will be a decreasing function of uncertainty of outcome, while its shape will resemble convex function where its lower bound is near the point where uncertainty of outcome is maximized. This hypothesis implies a U-shaped curvilinear relationship when uncertainty is measured by home team win probability (HWP), such that: **H1A:** \( \frac{\partial \text{Attendance}}{\partial \text{HWP}} < 0 \) and **H1B:** \( \frac{\partial^2 \text{Attendance}}{\partial \text{HWP}^2} > 0 \).

**H2:** Home attendance will be positively associated with home team quality. That is, attendance is an increasing function of home team quality, \( \frac{\partial \text{Attendance}}{\partial \text{HTQ}} > 0 \).
**H3**: Home attendance will be positively associated with away team quality. That is, attendance is an increasing function of away team quality, \( \frac{\partial Attendance}{\partial ATQ} > 0 \).

**H4**: Home attendance will be positively associated with the number or total wage bill of home team superstars. That is, attendance is an increasing function of number of home team superstars, \( \frac{\partial Attendance}{\partial HS} > 0 \).

**H5**: Home attendance will be positively associated with the number of away team superstars. That is, attendance is an increasing function of number of away team superstars, \( \frac{\partial Attendance}{\partial AS} > 0 \).

H1 refers to the uncertainty – or relative quality – of the match, H2 and H3 refer to the absolute quality level of the match, and H4 and H5 are expectations about the role of superstar effects.

Note that the first derivative of attendance with respect to home win probability determines the direction of the relationship, while the second derivative determines the shape of the relationship. This hypothesis, therefore, expects a U-shaped relationship between uncertainty and attendance.

The current approach highlights the importance of understanding the role of uncertainty not just in demand, but in the growth of new leagues looking to establish a footing in a crowded North American professional sports market. The work here extends this inquiry by testing the influence of team quality and win probability for MLS attendance in light of the league’s relatively unique talent distribution policy efforts in its aspirations toward sustained growth.

**Data and Methods**

The data used in the current study are comprised of all 2010–2015 MLS regular season games, resulting in 1,855 individual match-level observations collected from the MLS official
There were 16 teams in the league in the 2010 season, 18 teams in the 2011 season, and 19 teams during the 2012 to 2014 seasons due to expansion. Chivas USA folded after the end of 2014 season and two teams, Orlando City FC and New York City FC, were inaugurated, resulting in 20 teams in the 2015 season. Each team played 30 games in the 2010 season, but the season length was increased to 34 games in 2011. Schedules are unbalanced, with 24 intra-conference and 10 inter-conference games each regular season.

I measure game outcome uncertainty \((OU)\), using home team win probability \((HWinProb)\) and its squared term \((HWinProb^2)\) in the regression. The squared term is used to estimate a non-monotonic relationship between uncertainty and attendance (U-shape or inverted U-shape), as is standard in the literature. Fixed betting odds have been shown to improve estimation of uncertainty of game outcomes (Peel & Thomas, 1992). I therefore obtain home team win probability through the approach of Kuypers (2000), deriving the implied win probability from fixed betting odds collected from Covers.com. For instance, for positive betting lines, these can be converted into fraction odds by dividing the line by 100. In the case of negative betting lines, these can be converted into fraction odds by diving 100 by the betting line in absolute value. Then, I can derive the percentage of outcomes (i.e., home win, away win, draw) through following equation:

\[
\text{Outcome Percentage} = \frac{100}{(1 + Odds)}
\]

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2 I note that at the time of the data collection, the MLS website did not include game-level attendance data prior to 2010.
From these all outcomes, the over-roundness – the odd maker’s take – can be calculated by summing the percentage of outcomes and subtracting 100. Then, implied probabilities can be calculated through following equation:

\[ Implied\ Probability = \frac{1}{(1 + Over\ Roundness)(1 + Odds)} \]

Although Kuypers (2000) assumed that the over-roundness is fixed in the context of English Premier League, the data revealed that the over-roundness each game in the MLS is asymmetric. I have therefore used a dynamic measurement of over-roundness for each individual game to get the sum of the probabilities reach unity in the calculation above. For the ease of interpretation, I multiply the probabilities by 100 when entered into the regression estimation.

Home (HTQ) and away (ATQ) team quality are measured using an Elo rating of each team, updated after on the most recent regular season game outcome, an approach taken recently in Mills, Salaga, and Tainsky (2016). Recent work has shown that Elo ratings can be particularly useful in explaining team strength and quality of performance and do not suffer from seasonal timing issues as with traditional win percent, ranking, or conference standing measures (Binder & Findlay, 2012; Gasquez & Royuela, 2016; Hvattum & Arntzen, 2010). Most importantly, the measure allows the inclusion of margin of victory and opponent quality to determine changes within the dynamic estimate of individual team strength. While past work has used standings to establish team quality, the unbalanced schedule could bias standings and points totals, which also succumb to small sample issues early in the season.
To calculate MLS team Elo ratings, an adjusted version of the World Football Elo Ratings has been used in this study. The starting Elo ratings were initiated using goal differential from the 2008 season, and trained the ratings using the 2009 season such that they converge on reasonable values at the start of data in 2010. I use a starting average value of 1325 for each team and apply the following formula using the 2008 regular season goal differential results to arrive at starting Elo values for each team, \( i \), in 2009:

\[
ELO_i = 1325 + 1325 \cdot \left( \frac{d_i}{\sum |d_i|} \right),
\]

where \( d_i \) is the goal differential during the season for team \( i \). The starting values range from 1186 (Toronto FC) to 1541 (Columbus Crew) to begin the 2009 season. I use goal differential only as a proxy for starting values, as this reveals more information about gameplay and overall dominance of wins than the somewhat arbitrary points system awarded to wins, draws, and losses. Further, I use these values simply as a starting point to train the Elo ratings across the 2009 season to determine a starting value in 2010, when the data begins. This allows the measure to be less dependent on the ending season goal differential itself, and determined by goal difference-weighted individual game outcomes in 2009. Finally, as the Seattle Sounders were added to the league in 2009, they were assigned the average Elo of 1325 to initialize their rating. Any team that joined the league after 2009 was assigned the same 1325 average value to start their first game.

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3 A full description of these ratings can be found at www.eloratings.net.
I calculate Elo dynamically across the season by updating each team’s rating after each game played using the following formula:

\[
ELO_{i,\text{END}} = ELO_{i,\text{START}} + K_i^* (W_{ij} - Pr[W_{ij} = 1]).
\]

In this specification, \(ELO_{i,\text{END}}\) is the Elo rating for team \(i\) at the completion of the given game, while \(ELO_{i,\text{START}}\) is the starting value for the Elo rating for team \(i\) entering the game. \(W_{ij}\) represents the result of the game,

\[
W_{ij} = \begin{cases} 
1 & \text{if team } i \text{ wins} \\
0.5 & \text{for a draw} \\
0 & \text{if team } j \text{ wins}
\end{cases}
\]

and \(Pr[W_{ij} = 1]\) is the Elo based probability expectation for a win by team \(i\) calculated by:

\[
Pr[W_{ij} = 1] = \frac{1}{10^{ELO_{\text{diff}}_{ij}/400} + 1}
\]

\(ELO_{\text{diff}}_{ij} = ELO_{i,\text{START}} - ELO_{j,\text{START}} + 100 \times I \text{(i is Home team)}.\)
Finally, $K$ is a constant, set to 60.\(^4\) The $K$ parameter is adjusted, $K^*_ij$, for the goal difference in the game as follows (where $|d_{ij}|$ is the absolute value of the score difference in the game between home team $i$ and away team $j$):

$$
K^*_ij = \begin{cases} 
K & |d_{ij}| \leq 1 \\
1.5 \times K & |d_{ij}| = 2 \\
1.75 \times K & |d_{ij}| = 3 \\
(1.75 + \frac{|d_{ij}|^\frac{3}{8}}{8}) \times K & |d_{ij}| > 3 
\end{cases}
$$

I refer to home Elo rating as $HELO$ and away Elo rating as $AELO$ in the regression specification, and note that each of these is divided by 10 to assist in interpretability of the regression coefficients. As an additional measure of general competitive balance, I also include the league-level standard deviation in Elo, $sELO$. This is calculated at daily and included as a covariate for each game held on the subsequent day. I note that this is dynamic throughout the season and changes as games are decided from day to day.

To establish superstar effects, I include the total number of DPs for both the home ($HDP$) and away teams ($ADP$) in each season. I estimate alternative models that include the total salary of all DPs on a given team ($HDPSal$ and $ADPSal$), since the performance talent and superstar value of these players can vary dramatically these data were transformed into millions of 2015 dollars. DPs are defined by identifying those players with a base salary were over $335,000 in 2010–2011 season, $350,000 in 2012 season, $368,750 in 2013 season, $387,500 in 2014 season,

---

\(^4\) This is the value used for World Cup finals games by eloratings.net, as they are the most important games for international soccer teams. We assume that all regular season games reveal similar information about MLS teams, and therefore apply this $K$ constant in the MLS context. We acknowledge that rigorous testing of an optimal MLS-specific $K$ parameter would be a worthwhile paper on its own.
and $436,250 in 2015 season within the data (Coates, Frick, & Jewell, 2016; Mayers, 2014; Tannenwald, 2015). These high-earning players in the MLS can also be a relevant indicator of higher quality team, but may also reveal general fan interest in superstars (DeSchriver, 2007; Lawson et al., 2008). As noted previously, MLS allows each team to have up to three DPs; however, in the 2015 season, “targeted allocation money” from the new collective bargaining agreement has allowed each club to buy down players’ salaries at the maximum salary threshold for acquisition of an additional high earning player (McIntyre, 2015). Hence, the data shows that there are some teams with more than three players with salary above the cap, which are also identified as DPs.

The estimation also includes various control variables for the stadium, team, and market. These include home and away team age (HAge and AAge), home and away market median household income in thousands of 2015 dollars (HInc and HPop), population in thousands (AInc and APop), stadium age (StadAge and its associated squared term), and an indicator of whether the stadium is soccer-specific (SoccerStad). I also include indicator variables representing the weather on game day (clear, precipitation, or cloudy). Lastly, the existence of MLS Rivalry Cup games – similar to the rivalry matches well known in European competition – may also increase the demand for games among fans. I therefore include a dummy variable, Rivalry, equal to one if a game is one of the established MLS Rivalry Cup games, and zero otherwise. For instance, whenever DC United and New York Red Bulls (Atlantic Cup) compete with each other, I categorize these games as Rivalry Cup games. I note that this final estimation includes only U.S. based teams to avoid differences in the aggregation of population or income statistics in Canada relative to the U.S. Census data.

The empirical specification – without income or population – is specified as follows:
\[
\ln(Att_{gijt}) = \beta_0 + \beta_1 * HWInProb_{gijt} + \beta_2 * HWInProb^2_{gijt} + \beta_3 HELO_{git} + \beta_4 AELO_{gjt}
+ \beta_5 sELO_{gt} + \beta_6 HDP_{it} + \beta_7 ADP_{jt} + \beta_8 Rivalry_{ij} + \beta_9 SoccerStad_{it}
+ \beta_{10} StadAge_{it} + \beta_{11} StadAge^2_{jt} + \beta_{12} HAge_{ij} + \beta_{13} AAge_{it} + \beta_{14} HInc_{jt}
+ \beta_{15} AInc_{ij} + \beta_{16} HPop_{jt} + \beta_{17} APop_{ij} + \omega_g + \tau_t + \mu_g + \delta_g + \epsilon_{gijt}
\]

where \(i\) and \(j\) (\(i \neq j\)) represents competing home and away team in each game, \(g\), in year \(t\), respectively. Weather effects are represented by \(\omega_i\). Yearly effects are represented by \(\tau_t\), while monthly and day of week effects are included as \(\mu\) and \(\delta\), respectively. I use a panel Tobit correction to account for this right-censoring based on each individual game’s stadium capacity, and estimate the models using the natural log of attendance due to skewness in the attendance distribution and for ease of interpretation across teams with different levels of attendance.

While the specification above is a random effects (RE) estimation with respect to home and away teams, I also estimate models with dummy fixed effects for the home (\(\theta^H_i\)) and away (\(\theta^A_j\)) teams to control for unobserved heterogeneity across markets for robustness of the presentation. I note that unconditional dummy fixed effects in Tobit panel models may be biased and inconsistent. Further, a lack of season-to-season variation in absolute quality measures reduces the ability to estimate the effect of these variables in a short panel like ours when including home fixed effects (HFE) and home and away fixed effects (HAFE). I therefore focus on random effects estimates.

Additionally, while controlling for home quality is an important step in understanding the relationship between quality, win probability, and attendance (Pawlowski & Anders, 2012), Skrok (2016) notes that much of the confusion over the effects of uncertainty in previous work
could be a result of poorly separated quality and uncertainty measurements, obscuring estimates of the relationship between attendance and uncertainty. I therefore separately estimate identical regressions with only high quality home teams (those with Elo over the 1325 average team) and only low quality home teams (those with Elo below the 1325 average) to detect any structural differences in fan interest in uncertainty across high and low quality teams. However, nothing about the estimate of uncertainty of outcome changes by breaking the data into these subsamples. Therefore, I do not present these results, but note that they are available upon request.

Lastly, the Los Angeles based MLS team, Chivas USA, had attendance levels that were substantially below other teams in MLS, and folded in 2014. The team had a unique marketing strategy, focusing specifically on a Hispanic fan base in the Los Angeles area. However, given the findings of Jewell and Molina (2005), I assume Chivas home games are unique in that classical determinants of demand may not apply in the same way as for other teams. Therefore, given this unique positioning, I estimate the models with Chivas home games removed; however, I leave Chivas away games in the sample, since fans attending those games are most likely fans of that home team playing against Chivas. Indeed, regression results including Chivas home games had large effects on coefficient estimates. I did not find such large changes in coefficient estimates when excluding other teams individually from the sample, providing strong evidence that the team should be treated uniquely in future work.

**Results and Discussion**

Table 1 presents the descriptive statistics for all variables included in the regression estimation. It is clear that average U.S. MLS attendance has risen considerably during the time of the sample, from approximately 16,600 to 21,200 fans per game. There is considerable variability in the data, with attendance ranging from about 6,000 to over 62,000 fans. The average implied win probability for a home team is approximately 47.1%. Elo ratings ranged
from 995 to 1,640, while the daily standard deviation of Elo ratings ($sELO$) was approximately 100. Finally, teams have an average of 1.4 DPs, and rivalry games make up 8.2% of observations.

Table 2 presents the results of the regression estimations. All models include yearly, monthly, day of week, and home team fixed effects, and a total of 343 of 1,224 observations were right-censored due to sellouts. The coefficient estimates vary slightly in magnitude depending on the use of $HDP/ADP$ or $HDPSal/ADPSal$ in each model, but reveal nearly identical substantive results. Similarly, separate estimations using subsamples of only above average and only below average teams revealed $OU$ results consistent with all other models.\(^5\) I therefore focus the remainder of the examination largely on the random effects models for reasons posited earlier, and discuss the estimates in the context of their effect on the latent attendance variable for simplicity.

The most striking result from the estimation is that attendance follows the convex, U-shaped relationship with respect to home win probability, as predicted by Coates et al. (2014). This result confirms H1 through sub-hypotheses H1A and H1B. In other words, fans of MLS show attendance behavior consistent with either loss aversion or interest in at least one high quality team that has a high likelihood of winning the game over the other (Buraimo & Simmons, 2002; Mills, Tainsky, & Salaga, 2016). This effect estimate is in contrast to that found in Jewell (2017), though I argue that the use of outcome probabilities more accurately reflects uncertainty than point differences.

In Figure 2-1, I exponentiate the predicted logged attendance values from the regression for each game and fit a quadratic to the predicted attendance levels, along with a confidence

\(^5\) These additional robustness checks are available upon request.
interval around these predictions. As shown in Figure 2-1, attendance tends to decrease in
\( HWinProb \) between 0.10 and about 0.45, but begins increasing again when \( HWinProb \) is greater
than 0.45. More specifically, as \( HWinProb \) increases from 0.15 to 0.45, attendance is estimated
to decrease from nearly 27,000 fans to less than 20,000 fans. However, as \( HWinProb \) increases
from 0.45 to 0.75, attendance returns to approximately 26,000. I identify the bounds of the most
common win probabilities from the \( HWinProb \) distribution (Figure 2-2) using red vertical lines
in Figure 2-1. With the added fixed effects for home and away teams, there is some evidence that
– within the more common win probabilities – home fans simply prefer a higher home win
probability. However, this still refutes any claims of interest in game uncertainty, and the
estimates still show fans particularly interested in games featuring a high quality away team
either through \( AELO \) or implicitly in the probability of home defeat. Further, the measure of
general competitive balance in the league, \( sELO \), was not statistically significant in either model
in which it was included, again providing little evidence that general balance or game uncertainty
is of interest to MLS fans.

Moving to team quality, home Elo rating, \( HELO \), is positively related to attendance, also
confirming H2. Specifically, for each 10 point increase in \( HELO \), attendance increases by 0.2
percent. Going from the highest quality to lowest quality home team, as measured by \( HELO \) is
associated with a change in attendance of about 2,700 fans per game for the average 2015 team
attendance. Similarly, the coefficient estimate on the number of designated (superstar) players on
a home team is positive and statistically significant, as is the salary of these players in the
random effects model, confirming H4. The result is consistent with previous finding of
DeSchriver et al. (2016) which also used total number of DPs in home and away team to identify
the effect. This coefficient indicates that an additional DP on the home team, \( HDP \), is associated
with an attendance increase of 3.5% to 4.2%, or about 890 fans per home game for the average team attendance in 2015. However, there was no effect of home market income or population on attendance. This is most likely because of very short time period over which I estimate the regressions and high collinearity of these variables with home fixed effects when they are included in the model.

Away team Elo rating, $AELO$, is also statistically significant and positive, confirming H3. On average, a 10 point increase in $AELO$ is associated with an increase of 0.2% to 0.3%, similar in magnitude to $HELO$. The increase in attendance playing against a team with the highest $AELO$ in the sample relative to the lowest $AELO$ team, is about 3,375 fans using the middle of these estimates (0.25%). I feel that this result requires special attention, given the change to the statistical significance of the coefficient in the away team fixed effects context. Specifically, it is likely that away quality does not vary enough within team in the data to estimate its effect separate from the general fixed interest in each specific team. However, I note that part of the determination of a team fixed effect is likely its historical quality. While much of the literature assumes quality variations are exogenous from team fixed effects, I propose that researchers use care in choosing of variance (within or between) used to estimate team quality impacts on fan interest. For example, if historical quality and fixed effects are nearly perfectly collinear, there could be endogeneity issues related to estimation of team fixed effects in panel models. While Hausman tests can be useful in this instance, I suggest a possible interpretation of the fixed effect itself – as likely being determined by average quality and other “brand” related factors – is of use for understanding demand determinants. This would be particularly relevant if this brand creation is persistent over time through past on-the-pitch success. Coates, Feddersen, Naidenova, and Parshakov (2016) have begun taking the literature in this direction.
Away DPs, *ADP*, also have a statistically significant and positive impact on attendance, with each additional DP associated with an approximately 3.5% increase, or 740 fans per game. I find similar directional coefficient results with *ADPSal*. This confirms H5; however, the estimate is smaller than found in Jewell (2017). I note that the DP dummy classification is more liberal than in this past work, and therefore the effect would be expected to be smaller than estimates using only a few key marquee players. Contrary to the home team, I do find a statistically significant effect of the population of the market in which the visiting team resides, but only for those models using *HDP* and *ADP*, rather than the wage bill versions of these variables. The associated increase for each additional 1,000 people in the Away team’s market is approximately 0.13%, or 1.3% per million residents.

Moving to the additional control variables, I find no statistically significant effect of designated *Rivalry* matches or home and away team age on attendance in the estimations. However, I do find a negative relationship between attendance and the age of the stadium. For each additional year in age, attendance decreases by approximately 4%. However, I note that this effect is diminishing. Finally, I find little evidence that attendance is significantly related to soccer-specific stadiums with one of the models showing negative effect.

As a whole, these models provide evidence primarily for home team interest in home team quality and superstars, followed by interest in away team quality and superstars. These results may support the idea that there is an interest in attending a game even when home team is expected lose when a very high quality team visits. In that light, there may exist expectations of an upset where the underdog (home) defeats the dominant (away) team, resulting in high levels of utility for fans (Coates et al., 2014). Alternatively, a lower quality team might simply benefit from hosting a high quality, superstar-filled away team by seeing significant increases in
attendance, consistent with the findings of Mills, Tainsky, and Salaga (2016) in the NBA. However, the effects I present here are relatively modest: even extreme swings in home win probability result changes to attendance of 6,000 fans, holding constant the quality of the away team, while swings in attendance along the more common distribution of home win probabilities is about 2,000 fans. All in all, however, I find little evidence of interest in uncertainty of outcome among MLS fans.

With the recent expansion of MLS, soccer seems to be on an upward trajectory in North America with the league showing potential to become a mainstream major sport in the U.S. and Canada. In this context, the current study set out to develop an understanding of the behavior of fans and implications with respect to policies supposedly in place to enhance competitive balance and uncertainty of outcome. Specifically, while outcome uncertainty is often posited to be a worthwhile pursuit for sports leagues (Rottenbeg, 1956), there is evidence that superior teams and superstars may be particularly important for the growth and popularity of MLS, at least in terms of attendance (DeSchriver, 2007; Jewell, 2015; Lawson, Sheehan, & Stephenson, 2008). This contrasts with the findings of Paul and Weinbach (2013) for MLS broadcast viewership, indicating that these fan bases behave differently, or are distinct consumer markets as suggested by Mongeon and Winfree (2012) for the NBA. This contrast could indicate that the cost of attending MLS games makes fans more risk averse, while uncertainty is of interest for television viewership given the low commitment required for the latter.

Conclusions and Future Directions

The results here provide important insight into current league policy of the MLS. While the adoption of a single-entity may have been used to promote balance through centralized control, results indicate that the league has been well-served by also providing relatively
unbalanced matches and superstar players and teams. This highlights the possibility that in order to continue its growth, MLS may need to focus on increasing absolute talent and providing conditions in which certain teams become relatively dominant.

As Czarnitzki and Stadtmann (2002) point out, outcome uncertainty may not matter in MLS, where brand/reputation of a team or simply having a world class athlete in a team may be a key affecting element to the demand. I also find that home or visiting teams with high winning probabilities draw increased attendance. In other words, teams with great success (or finishing seasons in top standings) within the league is more likely to be attractive, and these teams may generally develop more notable brands or reputations that can help to grow league interest. I therefore leave this part of analysis for future studies incorporating brand or reputation effects to demand estimation, providing an opportunity for cross-disciplinary inquiry between economics, consumer behavior, and marketing. These effects may also be related to an interest in dynasties – rather than consecutive season uncertainty and turnover – a realization of balance I do not address in the estimations. I suggest future inquiry related to the various facets of uncertainty in future work.

It may also be that home fans may suffer from a “bold forecast” problem (Kahneman & Lovallo, 1993) described by Coates et al. (2014) as utility gain from upsets. Given that individuals tend to miscalculate the probability and risk of many scenarios by ignoring past information, they tend to reach biased future expectations and become overly optimistic about the prospect of their favorite home team winning a given game, underestimating the opponents’ relative performance or quality. Future studies could therefore benefit by integrating lessons from behavioral economics into models of fan interest and fan behavior. While this result is consistent with recent theoretical work from behavioral economics (Coates et al., 2014), future
studies are encouraged to test the validity of UOH across other major same-sport leagues in the U.S, and even across the international borders, as well as provide evidence for the specific motivation of home fans with respect to their interest away team quality.

Further, rivalries within MLS are not established at the level found in European leagues due to great distance between teams in general. Rather, the league-driven nature of these games during two designated rivalry weeks are externally ‘forged’ rival matches (Parker, 2015). Therefore, a closer comparison between artificial rivalry settings between actual fans’ perception of rivalry could cast better policy implication of beginning or growing professional league.

Lastly, Szymanski (2003) laid out institutional differences that exist between major professional leagues in the U.S. and European football leagues, such as the English Premier League, and how this could affect operation, organization, and league policy related to control over the distribution of talent. Yet there remains a gap in international sports comparisons from the demand perspective, particularly within the same sport (Bergsgard et al., 2007; Fort, 2000). Therefore, comparative analysis of the impacts of these league characteristics would seem central to evaluating heterogeneity in the validity of UOH. And these comparisons may be particularly helpful in understanding the validity of managerial implications of the findings of this work across international borders.
Table 2-1. Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
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<td>7,348</td>
<td>5,990</td>
<td>62,510</td>
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<td>16,596</td>
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<td>50,000</td>
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<td>7,357</td>
<td>8,224</td>
<td>50,000</td>
</tr>
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<td>85.50</td>
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<td>15.191</td>
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Notes: Data presented in this table excludes Chivas home games and any game featuring a Canadian-based team.
Table 2-2. Results of Tobit Regression

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<th></th>
<th>RE</th>
<th>RE</th>
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Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All models include home team, seasonal, day of week, and month fixed effects. N = 1,224 for all models, with 343 right-censored observations due to sellouts. Weather effects are included in all models, but were not statistically significant and are therefore not reported here.
Figure 2-1. Visualization of Curvilinear Relationship
Figure 2-2. Distribution of Home Win Probability
CHAPTER 3
LOCAL BROADCAST VIEWERSHIP IN MAJOR LEAGUE SOCCER

Introduction

Identifying what drives sports fans to consume games across various mediums is a central challenge for sport managers as the media landscape for live sport continues to evolve. Estimating the determinants of sports spectatorship demand has therefore played a central role in the literature within sport management and sports economics. In particular, much of the literature has sought to establish comprehensive fan demand functions to guide league and team strategies and policies regarding talent investment, scheduling, marketing, and management of sporting contest broadcasts. As revenue streams grow beyond gate receipts, academic work has moved toward more closely understanding the characteristics driving fans to television, in some cases in lieu of heading to the stadium. With the growth of broadcasting rights contracts, leagues have witnessed continuous increases in media rights valuation, advertising, and sponsorships, with broadcasting rights making up a much larger proportion of overall revenues than ever before (Tran, 2017). However, given the historical reliance on attendance to both generate revenues and engage fans in the excitement of the event, questions arise with respect to the tradeoff made by providing multiple – possibly competing – choices for fans to consume games.

Specifically, sports fans have two central options when consuming live sporting contests: attend the game at the stadium or watch the game through a television broadcast.\(^1\) One of the most salient differences across attendance and television broadcast consumption is the respective cost associated with each. Television (or streaming) viewers are less bound by time or financial

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\(^1\) We note that streaming viewership is becoming more common; however, I include this medium under a broad umbrella of television or screen viewership.
cost constraints when watching a game, avoiding the ticket, travel, parking, and concessions costs associated with attendance. Even when televised sport consumption may require a subscription fee, the marginal monetary cost of each game is near zero due to a relatively unrestricted number of games that one can enjoy and the bundling of games with other consumable sporting events on these channels. For example, Mongeon and Winfree (2012) noted that substantial time, travel, and ticket costs make switching behavior less likely among attendees than for television viewers, which have smaller levels of investment in consumption of the game. With lower costs to switching, viewers may be more likely to tune out if the game product is unsatisfying. Further, these authors show that consumers of broadcasts may have different preferences for certain game characteristics than those that attend the game. In other words, the large capture of revenues through newer media may result in a majority of fans more easily substituting the game product with other leisure options. Yet a divergence in interest among market segments could result in making different strategic managerial choices that ensure viewers remain tuned in. This, in turn, may reduce gate attendance, where fans derive excitement and are most likely become strongly attached to their local sports teams or begin habitual consumption (Lee & Smith, 2008; Spenner, Fenn, & Crooker, 2010; Won & Lee, 2008). Therefore, the expected magnitude of tradeoffs between consumption avenues may be used to guide managerial decisions.

However, research addressing both attendance and television demand for the same set of games has been limited, particularly so as it relates to Rottenberg’s seminal Uncertainty of Outcome Hypothesis (UOH). Specifically, Rottenberg (1956) posits that sports fans favor games with greater unpredictability, ultimately implying that preferences for sporting contests are dependent upon some level of competitive balance across teams in a league. However,
Rottenberg’s prediction was largely predicated upon game attendance as the primary consumption avenue, leading to a plethora of literature testing the theory in this context\textsuperscript{2}. There has also been empirical ambiguity with respect to support for UOH in the attendance setting, though more recent research using television ratings for the National Football League (NFL) has allowed an understanding of the importance of segmenting markets in understanding fan preferences for uncertainty and quality (Xu, Sung, Tainsky, & Mondello, 2015). In particular, when segmenting fans into winning, neutral, and losing market television viewers, winning markets are more likely to stay tuned into the game regardless of score margins. However, losing markets and neutral markets behave similarly in tuning out as the score margins increase, revealing interest in uncertainty among presumably neutral fans.

In light of this broader ambiguity, there is a need for further investigation of the determinants of demand for broadcast viewership on which to cast recommendations for leagues in nurturing future growth. This is particularly the case for new or developing professional leagues that depend on understanding the interests of fans as they seek to grow into mature organizations. Nonetheless, despite a growing literature on viewership demand for sport, there has been dearth of focus on Major League Soccer (MLS), a unique North American league in which policies and decisions are centrally controlled through its single-entity structure (Jakobsze, 2010). MLS has enjoyed slow growth through extensive expansion strategies and broadcast revenue growth, though there is continued skepticism over the necessity for this unique league structure (Késenne, 2015).

\textsuperscript{2} Villar and Guerrero (2009) provide an extensive review
Growth in both attendance and viewership has been widely reported for MLS. The league has witnessed an increase in its annual average attendance, drawing over seven million accumulated fans to the stadium by the end of 2016 season (Brisendine, 2016). There is evidence for recent growth in broadcasting revenue, as MLS signed new broadcasting deal with NBC Sports in 2011 for approximately $10 million annually, ending its previous deal with Fox Soccer (Bell, 2011). It has been reported that games broadcast under this contract had a total of 13.2 million viewers for the 2012 regular season, about three times the level of the previous contract with Fox Soccer (Tannenwald, 2012).

Nevertheless, only a single study has addressed MLS television viewership, and only using broadcast ratings at the national level (Paul & Weinbach, 2013). This dearth of inquiry has resulted in an inability to segment the market by home and away fans, as has been done in prior work in other leagues (Sung, Mills, & Tainsky, 2017; Xu et al., 2015). Given the niche market of MLS in U.S. professional sports, local broadcast viewership patterns are also of interest. Further, despite the well-known increase in average attendance for MLS teams, little is known about the general local viewership size across markets. This work, therefore, uses a proprietary data set on local MLS broadcast ratings to both establish the size of the MLS broadcast market, and to investigate determinants of demand for viewership.

I contrast the findings with the previous chapter estimating MLS attendance. In particular, I compare the results here to game quality effects on attendance, where fans showed more interest in games with greater certainty and high quality talent on both home and away teams. Further, I directly compare monthly viewership changes to monthly attendance changes from this past work, revealing evidence of switching behaviors from viewership to attendance and overlap in these two market segments. I also show extreme heterogeneity in market sizes
across MLS in the data. The findings suggest various directions for future research into the need (or lack thereof) for centralized control for the survival of new professional sports leagues, and future directions for investigation of MLS growth determinants.

**Literature Review**

**Outcome Uncertainty and Sports Demand**

Rottenberg (1956) first noted the importance of uncertainty of outcome and competitive balance in the survival of sports leagues, referred to as the UOH. These characteristics have long served as a central defense by the leagues in order to maintain cartel-like league structures and cooperative policies normally disallowed through labor and antitrust law. Given the prominence of competitive balance as a defense for these policies, sports economics research has centered upon understanding fan demand for uncertainty and balance. Specifically, if fans are not particularly concerned with competitive balance or outcome uncertainty, then there is little need for these policies.

The literature has conceptualized uncertainty of outcome in several ways in order to measure changes to, and fan interest in, game-level uncertainty, championship uncertainty, and consecutive season uncertainty or dynasties (Lee & Fort, 2008; Mills & Fort, 2014). Although there are clear needs for competition in sports leagues to be relatively fierce, more recent work has questioned whether Rottenberg’s UOH applies at the individual game level, particularly when fans are partial to only one of the teams (Coates, Humphreys, & Zhou, 2014). For example, fan interest in game-level uncertainty implies that fans will be less likely to attend a game if the home team is very unlikely or very likely to win, while maximized where a home team is slightly more likely to win than the away team. This implies an inverted U-shaped relationship between home win probability and attendance. However, a large body of literature on outcome
uncertainty and gate attendance has revealed mixed results with respect to fan interest in uncertainty (Szymanski, 2003).

For example, some empirical work on game-level uncertainty has revealed that home fans prefer seeing their team win, with an attendance maximizing point at a home win probability between 0.6 and 0.7 (Knowles, Sherony, & Haupert, 1992; Rascher, 1999). However, recent literature on outcome uncertainty has found evidence for home fan interest in large-margin home wins, or a U-shaped home win probability-attendance relationship, where gate attendance or revenue is maximized when the outcome of a game is deemed to be more certain in either direction (Beckman, Cai, Esrock, & Lemke, 2011; Buraimo & Simmons, 2008; Coates & Humphreys, 2010; Coates et al., 2014; Czarnitzki & Stadtmann, 2002; Lemke, Leonard, Tlhokwane, 2010; Mills, Salaga, & Tainsky, 2016). These disparities call for more careful consideration of the predictions of UOH in the context of game uncertainty.

Additional work has found that interest in uncertainty at the game level varies by market affiliation (Xu et al., 2015). Given this variation, sport managers must understand how individual consumers differ in their consumption patterns in order to properly cater to each market segment. To address these differences, and in recognizing the evolving consumption of sport, recent work has turned to broadcast ratings data to establish the relationship between classical demand variables and consumer interest in game broadcasts, which provides researchers with the ability to differentiate fans by market, unlike attendance data (Tainsky, 2010; Tainsky & McEvoy, 2012). Further, work has found that fan preferences differ among television viewers and game attendees, highlighting the need for additional inquiry into market heterogeneity depending on consumption method (Buraimo, 2008; Buraimo & Simmons, 2009; Cox, 2018; Mongeon & Winfree, 2012). As consumption, and its associated revenue streams, shifts more heavily in favor
of broadcasting and streaming, fully understanding this heterogeneity in consumer markets
becomes all the more relevant to sport managers seeking to maximize team and league
profitability.

**Television Viewership Demand**

Similar to the findings on gate attendance, the effect of game-level outcome uncertainty
on viewership demand is mixed. For example, Forrest, Simmons, and Buraimo (2005) found that
viewership was positively influenced by game uncertainty after accounting for home advantage
and team quality in the English Premier League (EPL), while an increase in the probability of a
home win or draw (and with higher expected scoring) was also found to attract more viewers
(Alavy, Gaskell, Leach, & Szymanski, 2010). Other work has provided evidence supporting the
UOH in the NFL, where overall team quality and relative team quality increased ratings (Paul &
Weinbach, 2007; Tainsky & McEvoy, 2012), and similar findings held for Bundesliga,
particularly as the season progressed (Schreyer, Schmidt, & Torgler, 2016). Further, Cox (2018)
found that EPL broadcast viewers prefer matches when the winning probability is more evenly
distributed, while gate attendees were more interested in likely home team wins. At the
international competition level, evidence suggests that closer FIFA rankings for the competing
teams increased viewership demand in Germany for friendlies, while both qualification and
tournament games were found to be unaffected by outcome uncertainty due to the importance
these games carry (Schreyer, Schmidt, & Torgler, 2017).

There exists additional empirical work finding the effects in contrast to Rottenberg’s
prediction, or no evidence of outcome uncertainty having an effect on viewership behavior in
either direction. For example, outcome uncertainty measures using the difference in home and
away team win probability show no effect on viewership of EPL games (Buraimo & Simmons,
leading economists to speculate that, over time, interest at the game-level has shifted from match uncertainty to the presence of star players. Also, Pérez, Puente, and Rodríguez (2017) found that outcome uncertainty did not matter for La Liga viewers except in cases when two of the most recognized teams – Real Madrid and FC Barcelona – were competing. Additionally, Paul and Weinbach (2015) found no effect of outcome uncertainty on NFL Sunday and Monday night game viewership levels, while work focused upon out-of-market NFL viewers showed a small effects in reverse of UOH predictions (Tainsky & Jasielec, 2014).

In addition to mixed results relating to outcome uncertainty for television demand, empirical work has shown that other traditional demand shifters for attendance tend to explain a major part of viewership behavior, but not always in the same direction or at the same magnitude. For example, Tainsky (2010) found that income is negatively associated with television viewership of NFL games. Further, Mongeon and Winfree (2012) found that while winning percentage of a team up to the current game matters for both attendance and viewership demand, television viewers were more susceptible to the variation in winning percentage. Related inquiry has found that the presence of star athletes or teams with greater talent also had a positive effects on viewership (Buraimo & Simmons, 2015; Forrest et al., 2005; Hausman & Leonard, 1997), that viewers prefer games with higher expected scoring across multiple leagues (Alavy et al., 2010; Paul & Weinbach, 2007; Salaga & Tainsky, 2015), that matches featuring a local team’s rival are of higher interest (Sung et al., 2017), and that there is clear interdependence between local team success and viewership of out-of-market games (Tainsky, Xu, Mills, & Salaga, 2016; Tainsky, Xu, Salaga, & Mills, 2014).

An especially important factor to consider in identifying television viewership patterns – as opposed to game attendance – is that there exists an abundance of substitutes with low
switching costs to television. Mongeon and Winfree (2012), for example, found that existence of
other NBA teams and other indirect substitutable products decreased both attendance and
viewership demand. Tainsky and Jasielec (2014) also investigated demand for games without
local teams in the NFL, finding decreased viewership when within league games were
simultaneously broadcasted. Furthermore, when a game is also aired live on the television, there
was a decrease in EPL attendance demand, providing evidence of substitution between two
consumption avenues (Cox, 2018). Alternatively, Mills, Mondello, and Tainsky (2016) found
that MLB teams sharing markets benefit from success of the other, which was not the case for
the NFL (Mondello, Mills, & Tainsky, 2017), indicating differences in fan preference across the
leagues. They further found that in both MLB and the NFL, ratings are higher for games played
at home. Each of these findings provides critical direction on how leagues should schedule
games in the face of direct and indirect substitutes in order to maximize overall league welfare.

**Demand for Major League Soccer**

Jewell and Molina (2005) were one of the first to estimate demand for MLS games. They
found little support for fan interest team quality or the presence of Hispanic populations with
respect to gate attendance, but did exhibit that fans tended to substitute between the NFL and
MLS. While this substitution took place across leagues, more recent work has shown that two
nearby MLS teams tend to operate as strategic complements to one another, increasing
attendance when located close together (Wooten, 2018). Additional empirical inquiry has
revealed evidence for increased attendance due to novelty effects (DeSchriver, Rascher, &
Shapiro, 2016) and mixed attendance effects with respect to rivalry exhibited in the previous
chapter and in Jewell (2017).
Due to the unique nature of the MLS DP rule, empirical work has been particularly focused upon estimating superstar effects within the fan demand function. DeSchriver (2007), Lawson, Sheehan, and Stephenson (2008), and the previous chapter found positive effects of DPs on attendance demand for MLS games. However, Jewell (2017) found diminishing returns of this effect over time, and noted that this effect is largely specific to only a few of the league’s superstars. Furthermore, the superstar externality was particularly pronounced for David Beckham – the league’s first payroll exception – during road games (Shapiro, DeSchriver, & Rascher, 2017). Additionally, the resulting asymmetric salary distributions due to the introduction of DP rule were found to have a negative effect on overall team productivity (Coates, Frick, & Jewell, 2016). Hence, there seems to be a tradeoff between on-field performance and superstar interest when seeking to attract fans.

There has been much more limited inquiry into television viewership determinants for MLS. Only Paul and Weinbach (2013) have investigated determinants of MLS game broadcast consumption. This work found evidence supporting the uncertainty of outcome hypothesis in MLS, but was specific to national broadcast ratings on only a single year’s worth of observations. Given the dearth of work in this area, there are two foci requiring further investigation pertaining to viewership demand for MLS. First, investigation of the relationship between uncertainty and viewership is needed to establish a more rigorous test in MLS. These results can also be compared with attendance demand study to identify heterogeneity in effects of certain game and market characteristics. Second, inquiry into local market viewership, and separating fan allegiance by location of viewers, can provide a more thorough understanding of broad consumer interest as the league continues its expansion. I address these gaps in the literature with this work.
Conceptual Framework

As is standard in the literature, demand for sport is assumed to be affected by income, population, prices, the goodness and prices of substitutes, team quality, and the competitiveness of the league. The conceptual framework in this study also uses this general function, assuming that viewership demand is defined by a general demand function:

\[ Ratings = f(RQ, AQ, GC, E) \]

where the Ratings are a function of uncertainty or relative quality \( RQ \), absolute quality \( AQ \), other game characteristics \( GC \), and economic characteristics \( E \). Each of these characteristics can include various variables such as weather \( GC \), home win probability \( RQ \), home and away team quality or records in the standings \( AQ \), and local population and income \( E \). Given that broadcast or cable viewership is largely cost free – or any costs have already been incurred through the purchase of a television and cable subscription for various other programming – I exclude price from the demand model. Further, prices have long been empirically shown to behave unpredictability in sports demand models due to the various considerations that go into pricing the experiential product (Fort, 2004; Krautmann & Berri, 2007).

Relative quality for the purposes of this viewership demand inquiry refers to the closeness of competition at the game-level. Absolute quality then refers to accumulated team performance or current season performance. Although the league as a whole could suffer from the occurrence of a single dominant team, it is likely that fans prefer their local team to be at least slightly better than the competition (Knowles et al., 1992; Neale, 1964; Rascher, 1999). Further, there is prior evidence that local fans also have interest in high absolute quality away
teams (Mills, Salaga, & Tainsky, 2016; Coates, et al., 2014), which was found in the previous chapter as well.

I note that game characteristics can include information on weather, superstars, or the time of day in which the game is televised. As with past work, I hypothesize that superstar athletes will have significant and positive impact on the viewership (DeSchriver, 2007; Hausman & Leonard, 1997; Jewell, 2017; Lawson et al., 2008) and rivalry (Alavy et al., 2010; Forrest et al., 2005; Sung et al., 2017). Additionally, I expect higher ratings for games scheduled during primetime, for teams in older stadiums, and for teams with a longer history in their respective market. Lastly, I hypothesize that local sellouts or poor weather will increase broadcast ratings for home markets. Specifically, the broadcast of a game on television may absorb excess demand beyond the local stadium’s capacity, or allow for alternative consumption when viewing quality goes down due to poor weather. The latter implies that broadcast viewership may serve as a direct substitute to game attendance in certain situations. I formalize the estimation of this demand model in the following section.

**Data and Empirical Model**

For this study, I collected Nielsen Local People Meter live game average ratings for 1,514 televised MLS regular season games from 2010 to 2014 season. Ratings are recorded at the local market level for all markets playing host to an MLS team appearing in the televised game observation. Data from Nielsen are recorded as percentages with up to two decimal points, with ratings representing the average proportion of the local market that tuned into the game. For example, if a game receives a rating of 1.0, this means that an average of 1 percent of the local market was tuned in during the broadcast. If the local population is 2,000,000, then this would imply approximately 20,000 viewers tuned into the game at any given time during its broadcast.
Of all game-market observations available from Nielsen, 131 had ratings recorded as missing and these games were removed from consideration, as were those games without betting odds available to calculate win probabilities. I include both home team and away team market ratings, giving dual observations for most games, leaving 921 home market observations and 902 away market observations.\(^3\) There were total of 15 markets included in the data set for analysis.\(^4\) Canadian market data are not included, and I also remove the Columbus market due to issues with missing viewership data. Within the remaining U.S. markets, Los Angeles was the only market that played host to multiple MLS teams.\(^5\)

Within the sample period, the league consisted of 16 teams in 2010, 18 teams in 2011, and 19 teams in 2012. Each team played 30 games in 2010, which increased to 34 games in 2011. Teams have been divided into two conferences, Eastern and Western conference. In 2010, each team had a balanced schedule competing against one another twice at home and twice away. However, since 2011, teams have had an unbalanced schedule such that each plays 24 within-conference games and 10 out-of-conference games. Regular season games are played from March through October, then 12 teams (8 teams in 2010) advance to playoff competition.

I partition the data into two separate data sets: one includes only fans watching home games of their respective local team and the other includes only fans watching away games of their respective local team. Ratings include national and local broadcasts in the local market, as

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\(^3\)We note that games featuring a Canadian away team only include a single ratings observation for the U.S. home market.

\(^4\)Markets include Boston, Chicago, Columbus, Dallas, D.C., Denver, Houston, Kansas City, Los Angeles, New York, Philadelphia, Portland, Seattle, San Jose, and Salt Lake City.

\(^5\)Chivas USA folded at the end of 2014 season while L.A. FC has replaced the vacancy as of the 2018 season. New York City FC did not begin play in MLS until 2015, and therefore the New York Red Bulls do not share a market during the timespan of the data used in this work.
well as Spanish language broadcasts where applicable. Within the sample period, some of the games were featured on both national broadcast and cable channels, or simultaneously broadcasted on a Spanish language channel. In the cases where a game is broadcasted simultaneously on multiple channels, I sum ratings for the broadcast, while using ratings weighted by run time for games aired on different channels with differing recorded start and end times. Descriptive statistics for local game ratings are presented in Table 1 along with all other variables.

The natural log of home and away average Nielsen ratings for each game were used as the dependent variable in two nearly identical regression models to compare viewership behavior between home fans of home market (HomeMktRating) and away market (AwayMktRating) as follows:

\[
\begin{align*}
(1) \quad \ln(\text{HomeMktRating}_{gijt}) &= \beta_0 + \beta_1 \times \text{WinProb}_{gijt} + \beta_2 \times \text{WinProb}^2_{gijt} + \\
&\quad \beta_3 \text{HELO}_{gijt} + \beta_4 \text{AELO}_{gijt} + \beta_5 \text{sELO}_{gt} + \beta_6 \text{HDP}_{lt} + \beta_7 \text{ADP}_{jt} + \beta_8 \text{Rivalry}_{ij} + \\
&\quad \beta_9 \text{HLagWinPct}_{gl} + \beta_{10} \text{Cable}_{gij} + \beta_{11} \text{Primetime}_{gij} + \beta_{12} \text{HAge}_{lt} + \beta_{13} \text{AAge}_{jt} + \\
&\quad \beta_{14} \text{StadiumAge}_{it} + \beta_{15} \text{Sellout}_{it} + \beta_{16} \text{HInc}_{it} + \theta_i + \omega_g + \tau_t + \mu_g + \delta_g + \epsilon_{gijt} \\
\end{align*}
\]

\[
\begin{align*}
(2) \quad \ln(\text{AwayMktRating}_{gijt}) &= \beta_0 + \beta_1 \times \text{WinProb}_{gijt} + \beta_2 \times \text{WinProb}^2_{gijt} + \\
&\quad \beta_3 \text{HELO}_{gijt} + \beta_4 \text{AELO}_{gijt} + \beta_5 \text{sELO}_{gt} + \beta_6 \text{HDP}_{lt} + \beta_7 \text{ADP}_{jt} + \beta_8 \text{Rivalry}_{ij} + \\
&\quad \beta_9 \text{ALagWinPct}_{gl} + \beta_{10} \text{Cable}_{gij} + \beta_{11} \text{Primetime}_{gij} + \beta_{12} \text{HAge}_{lt} + \beta_{13} \text{AAge}_{jt} + \\
&\quad \beta_{14} \text{Sellout}_{it} + \beta_{15} \text{AInc}_{jt} + \theta_j + \omega_g + \tau_t + \mu_g + \delta_g + \epsilon_{gijt} \\
\end{align*}
\]
Here, \( i \) and \( j \) \((i \neq j)\) represents the home and away team in each game \( g \), in year \( t \). I estimated home and away ratings using (anchor) team fixed effects panel models. Note that the away market regression does not include StadiumAge, as away fans are unlikely to have the opportunity to attend a game, and therefore stadium quality is unlikely to have any impact on viewership behavior in away markets. Fixed effects panel estimation are used for each the home and away models with White’s standard errors robust to heteroskedasticity.

I measure outcome uncertainty using the probability of the viewing market’s local team winning the game (WinProb) derived from betting odds from Covers.com as in Chapter 2, and adapted from Kuypers (2000). This measure – paired with its squared term – allows a directional understanding of interest in uncertainty for both the home and away viewers.\(^6\) This poses the test for UOH in the model, with the classical prediction implying an inverted u-shaped relationship between viewership and WinProb.

Next, to control for the absolute quality of teams competing in a game, I use Elo ratings of each the home and away team, as represented by HELO and AELO. The model also contains the league-level standard deviation in Elo to control for variations of broader changes in balance across the league, sELO, which is calculated at the daily level. Elo estimates come directly from the work of Chapter 2 for the specifics of the calculation and more details on its usefulness in measuring absolute quality of teams across the season (Peeters, 2018). Elo is calculated directly from individual game outcomes across MLS seasons, and initially trained on the 2009 season,

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\(^6\) I have also estimated uncertainty using the Theil Index to capture the spread of all probable outcomes. However, in order to estimate models more consistent with Chapter 2, and given null findings with respect to this measure, I do not report the results of these models here. They are available upon request.
just prior to the start of the data. I divide all Elo measures by 10 for interpretability of the coefficients.

The model also includes variables to measure superstar effects as the total number of DPs for each the home and the away team, represented by $HDP$ and $ADP$, collected from mlsplayers.org. MLS rivalry games are represented by $Rivalry$, which are designated by MLS and collected from the MLS official website, mlssoccer.com. Team age is represented by $HAge$ and $AAge$. In terms of economic characteristics of each market, local market metropolitan statistical area average household income is included as $HInc$ or $AInc$ in 2015 constant dollars, collected from the U.S. Census. The population of each market, however, was not included due to concerns over the relative size of percentage growth of the local market and growth of viewership levels, making observations across seasons inconsistent.\footnote{Specifically, new residents to an area are unlikely to instantaneously become fans of the local MLS team. Therefore, viewership as a proportion of the market size would not be constant with population growth, which the ancillary models with population included show. This was also found by Tainsky and Stodolska (2010) in the NFL.} To control effects of broadcast characteristics, the model includes $Cable$ for any games that were featured on cable channels, and $Primetime$ for games that started between 19:00 and 21:45 in a given market. Home (Away) team fixed effects are represented by $\theta_i$ ($\theta_j$), yearly effects by $\tau_t$, and monthly and day of week effects by $\mu$ and $\delta$, respectively.

Additional variables are included to control for other expected effects of game day characteristics in determining viewership choices. $StadiumAge$ is included to capture the effect of aging or lower quality stadiums on driving fans from the stadium to broadcast viewership, with the year of construction and capacity of each stadium collected from worldfootball.net. I assume more fans would choose to watch games on television, rather than through game attendance, as
older stadiums become less desirable over time. Further, I include an indicator variable for sellout games, *Sellout*, where attendance is equal to stadium capacity to capture the presence of excess demand that may be captured through television viewership in sellout situations. Lastly, I include weather effects to capture this exogenous factor affecting consumer choice, represented by \( \omega_g \). There are three levels for this variable – *Clear*, *Cloudy*, and *Precipitation* – with a base level of *Clear*. This data was collected directly from box scores on the MLS official website.

**Results and Managerial Implications**

The descriptive statistics presented in Table 1 show that overall average ratings of MLS have steadily increased from 2010 to 2014 for both home and away games. The average ratings for home and away games are 0.57 and 0.52, respectively, or about 11,000 viewers in a market of 2 million. The higher home rating is consistent with past findings in NFL and MLB (Mills et al., 2016; Mondello et al., 2017; Tainsky, 2010). Ratings levels across individual markets are particularly disparate (Table 2), with the most watched team, the Seattle Sounders, receiving an average rating of 2.44 in 2014 (nearly 90,000 estimated viewers in the Seattle metropolitan statistical area), and the least watched team in the data, the New England Revolution, with an average 2014 rating of 0.12 (less than 7,500 viewers in the Boston-Providence metropolitan statistical area). Consistent with home field advantage, home teams have an average win probability of 47 percent while away teams average 28 percent.

Table 3 presents the results of coefficient estimates in the panel regressions for the determinants of viewership for home and away games. Table 4 presents the results of other control variables and dummy effects for each model. Results reveal slightly lower variance
explained to past work estimating television viewership with similar independent variables (Tainsky, 2010).8

Beginning with the key variable regarding game considerations, I find no evidence of viewer interest in uncertainty of outcome for home or away viewership, and at most, weak evidence that away markets are interested in more certain outcomes in favor of their own team (WinProb). This contradicts predictions of UOH at the game level, and also contradicts the findings for MLS attendance in the previous chapter that showed higher attendance at games with more certain outcomes. This supports evidence of the existing heterogeneity in preferences when consuming sporting contests in two related consumption markets, live game attendance and television audience, as noted by Mongeon and Winfree (2012). The result is quite different, however, from recent work on television broadcasts in other leagues that find viewers of games on television show more interest in uncertainty than those attending games, possibly due to risk aversion (Coates et al., 2014; Cox, 2018; Mongeon & Winfree, 2012). These results are also in contrast to previous findings of MLS viewership preferences for outcome uncertainty (Paul & Weinbach, 2013), but may have to do with the different samples: the prior work used national broadcasts – with more neutral fans – while I use local broadcast ratings, featuring fans that are likely to have a stronger preference for a given team in the match.

While there are no effects of overall league balance (sELO), there do exist positive effects of team quality (HELO and AELO), and the effect sizes for home and away viewers are similar in magnitude. For instance, a 100-point increase (about one standard deviation in the sample of Elo ratings) in the home or away team’s Elo rating increases viewership by about 9 to

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8 We note that ancillary models using raw ratings showed nearly identical variance explained to this past work.
10 percent. I put these estimates in the context of both the average city-level (approximately 1.9 million residents) and metropolitan statistical area (MSA) population of the local market (approximately 7.1 million residents), and as the change from the average rating in the data. At the city level, there is an expected change of about 1,115 viewers in home markets and 925 viewers in away market cities. At the MSA level, the purported increases are associated with 4,165 and 3,460 for home and away markets, respectively. Therefore, I find strong evidence to support the hypothesis that local fans prefer higher quality local teams. However, there is little evidence that prior year performance is a strong indicator of current season viewership, as measured by the win percentage from the previous year.

With respect to opponent externalities, I do not find increasing viewership in the face of higher quality away teams, even after controlling for home win probability, contrary to the findings of the previous chapter with attendance. However, the models indicate considerable superstar externalities from DPs on opposing teams. In particular, home viewership increases by 5.9 percent per DP featured on the away (ADP), while away viewership increases by 6.4 percent per DP features on the home team (HDP). In terms of raw viewership, each away DP is associated with an increase of 640 and 2,390 viewers in the home city and MSA, respectively. For the away team, the city and MSA viewership change from each additional home DP are about 635 and 2,370, respectively. This supports the idea that MLS uses these players in a way that improves visibility of the league, and that each team receives a considerable viewership externality created by the opponent’s superstars.

The home market model exhibits a positive effect of sellout games (Sellout) on broadcast viewership of these same games. I use the away market model as a falsification test of this variable picking up generalized high interest in these games, and there was no discernable effect
of game sellouts on viewership when the team is away. Therefore, I interpret the home sellout effect as broadcasts capturing excess demand after stadium seats are no longer available. This effect is estimated to be a 19 percent increase in home market viewership during sellouts, or about 1,915 additional viewers tuned into these games in the average city market in the data set.\(^9\) I base the substitution estimates on this smaller population, given the higher availability of attendance to this population closer to the stadium. However, at the MSA level, the increase in viewership from sellouts implies 7,160 additional viewers in the home market.

Similarly, I find likely substitution of broadcasts for attendance in the face of poor weather conditions. The home model estimates that in cloudy weather, broadcast viewership increases by 9.8 percent, and when there is precipitation, viewership increases by 23 percent, relative to clear weather. These are associated with increases of 1,060 and 2,495 viewers, respectively, in the average city market. Although these effects could be interpreted as a generalized increase in television viewership due to poor weather (substituting directly from outdoor activities), I find no effect of weather on away team market viewership. This falsification test again implies that the additional viewers are likely to be almost exclusively made up of fans that would have otherwise attended the local MLS game. This finding is inconsistent with the findings in the previous chapter, which found no statistically significant effects of weather on attendance levels. However, I note that the number of viewers for the average MLS game in the data is smaller than reported attendance levels. Therefore, these effects

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\(^9\) I note that I interpret the effect as the change from no sellout to sellout, which for dummy variables with a logged dependent variable, requires additional exponentiation. Specifically, dummy variables cannot be interpreted in the standard log-level fashion of multiplying the coefficient estimates by 100 to get the percentage change. The reader is referred to Kennedy (1981) for a full exposition of the appropriate exponentiation and interpretation of dummy variables in a log-level regression estimation. I use this approach for the exposition of all dummy effects discussed in this section.
would be expected to be larger, relative to total viewership. Further, teams likely report ticket sales, rather than gate attendance, therefore counting anyone who had already purchased a ticket to the game, but decided not to attend. This leaves opportunities for future research into MLS no-shows and the role they may play in impeding revenue generation for MLS teams as they attempt to grow their market. I propose that television ratings for these games are picking up on both lowered ticket purchases at the gate, and previously purchased tickets that result in no-shows in poor weather that are not netted out of gate attendance.

Next for the control variables, I find that home and away ratings have increased dramatically over the time of the data set. The change in home ratings from 0.45 to 0.72, and away ratings from 0.42 to 0.67, from 2010 to 2014 are approximately a 60 percent increase overall. At the MSA level, this is about 19,170 fans per game, and 5,130 at the city level for home games. For away games, the associated changes are 17,750 and 4,790, respectively. I also observe that games featured on cable channels had ratings 33 to 37 percent lower than broadcast channels without subscription fees. Given this, future MLS broadcasting contracts may want to consider the level of awareness of the local team when choosing to show games on cable or broadcast networks. As local broadcast channels may be easier to find for casual fans, this availability may substantially improve viewership for MLS teams. Similar to Paul and Weinbach (2013), I find no statistically significant effect of Primetime games in the data at the local level.

Most strikingly, the monthly effect estimates for MLS ratings for home markets are in reverse of those found in Chapter 2. Specifically, the previous work on attendance found that attendance increased over the course of the season, and particularly so in July, August,
September, and October.\textsuperscript{10} I estimate that home market viewership decreased by 21, 22, 25, and 37 percent for these months, respectively, while similar decreases did not take place in away markets. I use the city level market size to compare effect sizes, as it is likely that those within the city boundaries have easier access to the stadium and are more likely to attend than those further out in the MSA. Figure 3-1 presents the home effects with the coefficient magnitude of the non-significant monthly away effects netted out. Using this average market size of about 1.9 million city residents, and the average home rating in the data of 0.57, these estimates imply a loss of approximately 1,467, 1,583, 2,097, and 3,197 viewers for each of these months, respectively, relative to viewership levels in March. Estimates from Chapter 2 imply approximate increases to attendance in these same months of 1,683, 987, 1,094, and 2,875, respectively. I presume that a large portion of this increase comes from viewers early in the season substituting attendance for broadcasts as the season progresses, with a particularly stark effect in October as shown in Figure 3-1. This interpretation is supported by the lack of effects for away markets, given that there is no opportunity for substituting attendance for viewership in those games.\textsuperscript{11}

Although there is a net negative effect on away viewers in October, the magnitude of this coefficient is only about half that of the home market effect. Further investigation into the waning interests in broadcast viewership for MLS is recommended, particularly as it relates to

\textsuperscript{10} August attendance changes were statistically significant only at the 10\% level in Chapter 2, while the viewership estimates are statistically significant at the 5\% level. While I did not present monthly effects in the paper, these were available upon request. I used the monthly effects estimates with a baseline of the average reported attendance of 18,757.

\textsuperscript{11} All away market effects were not statistically significant, though they also showed a negative coefficient estimate direction. If I assume the substitution effect for home teams is the difference in the home and away coefficients, the respective changes would be 1,520, 1,657, 2,281, and 3,721 for July, August, September, and October, respectively. These estimates are closer to those found by the past work on MLS attendance.
local position in league standings and likelihood of making the playoffs. Although it could be that MLS teams face more competition from the Major League Baseball playoffs, the start of the NFL season, or National Collegiate Athletic Association football games in September and October, the previous chapter identified attendance increases during this same time. This finding could suggest that attendance at MLS games could be less sensitive to alternative options than is television viewership; however, the lack of effects in away markets seems to validate the television-attendance substitution hypothesis late in the season.

This type of substitution would be consistent with the predictions of Coates et al. (2014), noting that fans may be particularly risk averse with respect to attendance in the face of uncertainty about their local team’s quality. However, as the season progresses, additional information about the playoff picture and local team quality is revealed, decreasing the uncertainty in the expected seasonal outcomes, and therefore possibly leading in local fans to be more willing to take on attendance costs. Recent work from Cox (2018) provides further support for this interpretation using EPL attendance and viewership. In MLS, it seems that encouraging more certainty at the local level would be preferred, given the relative sizes of the changes in the two consumption avenues.

Consistent with the previous chapter, there was no estimated effect of MLS rivalry games (Rivalry) on viewership, rejecting the standard expectations related to rivalry effects. Recent work has noted the difficulty in defining rivalry (Tyler, Morehead, Cobbs, & DeSchriver, 2017), and the rivalry games are particularly manufactured in MLS. As it was previously found that current rivalry settings of MLS also did not affect attendance, the league may look to redefine its rivalry games, or allow them to develop naturally. Wooten (2018), for example, points to regional rivalry as a fruitful direction for league growth.
Finally, older teams (HAge and AAge) were associated with lower viewership. This is in contrast to the initial hypothesis. This could imply that MLS teams are drawing more fans to the stadium, losing fans over the course of time, or that the variable is simply picking up a large novelty effect for new expansion teams. Much of this effect may also be associated with the large ratings in Seattle relative to other teams. StadiumAge was not a predictor of home team broadcast viewership, providing little evidence for substitution between attending games at an aging stadium (poorer quality experience) and viewing on television. This latter result provides support for the novelty effect hypothesis.

Consolidating the results for the relative and absolute quality measures in the analysis indicates that outcome uncertainty does not matter much for viewership demand. However, both local team quality and opponent superstars are of central interest to fans, as revealed in previous literature on attendance (DeSchriver, 2007; Hausman & Leonard, 1997; Jewell, 2017; Lawson et al., 2008). These results cast critical questions on the current operation and policy of MLS. In particular, centralized control of MLS and its labor market exists under the guise of controlling balance of its member teams, presumably in the interest of consumers. However, this argument seems to have little ground for the favorable antitrust treatment the syndicate has received thus far. Ultimately, the entity status of MLS may be maximizing league welfare at the cost of consumer and player welfare. If fans do not care about balance, and prefer more superstars and absolute quality, then restricting the number of DPs on each team and dis-incentivizing player investment negatively impacts both players and consumers, while providing little alternative value to either. Although the MLS’s effort in reducing the cost of players is also in seeking to prevent the recurrence of an event like the folding of the North American Soccer League
(Francis & Zheng, 2010), it seems that current policies may need to be revisited to grow additional interest in the league.

### Conclusions and Suggestions for Future Research

Despite some cynicism that exists for the prospects of MLS in the long run, I show evidence of strong growth in viewership in professional soccer within the U.S. As the league’s commissioner Don Garber said, MLS is thriving over the last decade in both attendance and viewership (Baxter, 2015). Yet, determinants of viewership demand for MLS have been lacking greater scrutiny, particularly at the local market level. I provide insight into consumers’ behavior with respect to the choice to view games on television.

These results imply that MLS broadcast viewers are not particularly interested in outcome uncertainty, often claimed to be a central reason for the league’s unique structure and retaining and attracting fans. Alternatively, incentivizing teams to win more games and increasing the total number of superstars may enhance overall fan interest. Hence, the current league design claimed to encourage competitive balance with modest labor investment may hamper further growth. However, this result is nuanced. As the work here only establishes effects of game uncertainty at the game level – rather than interest in playoff races or dynasties – I suggest caution in making sweeping conclusions about MLS fans. Indeed, the monthly dummies indicate the possibility that fans substitute attendance for viewership late in the season when playoff and standings outcomes are more salient. Further, I do not have access to within-game changes to uncertainty, an important consideration with understanding how fans perceive the excitement and suspense of the game (Alavy et al., 2010). The strategy of investing in superstars seems to be fruitful for MLS both in the stadium and for broadcasts, though I note that promotion of these superstars tends to largely affect opponent market broadcast viewership.
Future research related to promotional strategies with respect to DPs and externalities is suggested, given this result.

The most unique contribution of the work here relates to evidence of substitution behavior of MLS fans in choosing the consumption options. Of course, although game attendees and live game television viewers show different preferences towards some game characteristics (Mongeon & Winfree, 2012), it seems that there also exists some overlap of consumers across the two consumption options. Due to the relatively small size of both viewership and attendance in MLS, apparent substitution is detectable in game ratings for home markets. These results provide important guidance on revenue priorities and cannibalization of attendance and broadcast contracts as the league moves forward, while also considering the complementarities that may exist (Zhang, Pease, & Smith, 1998). Furthermore, offering stadiums that provide protection of unpleasant weather may have a substantial positive influence on attendance. Future work would be well served to more closely identify fan preferences with respect to stadium and service quality as MLS continues to grow.
### Table 3-1. Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Home</th>
<th></th>
<th></th>
<th></th>
<th>Away</th>
<th></th>
<th></th>
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<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Min</td>
<td>Max</td>
<td>Mean</td>
<td>SD</td>
<td>Min</td>
<td>Max</td>
</tr>
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</tr>
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<td>0.526</td>
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<td>1.089</td>
<td>-4.61</td>
<td>1.43</td>
<td>-1.18</td>
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<td>0.098</td>
<td>0.100</td>
<td>0.760</td>
<td>0.278</td>
<td>0.085</td>
<td>0.110</td>
<td>0.670</td>
</tr>
<tr>
<td>LagWPct</td>
<td>0.518</td>
<td>0.106</td>
<td>0.191</td>
<td>0.706</td>
<td>0.519</td>
<td>0.105</td>
<td>0.191</td>
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<tr>
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<td>15.20</td>
<td>48.46</td>
<td>108.42</td>
<td>78.03</td>
<td>14.82</td>
<td>48.46</td>
<td>108.42</td>
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<td>1340.7</td>
<td>95.9</td>
<td>995</td>
<td>1631</td>
<td>1328.7</td>
<td>101.4</td>
<td>995</td>
<td>1631</td>
</tr>
<tr>
<td>HAge</td>
<td>12.54</td>
<td>5.98</td>
<td>1.0</td>
<td>19.0</td>
<td>11.49</td>
<td>6.28</td>
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<td>19.0</td>
</tr>
<tr>
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<td>1.02</td>
<td>0.0</td>
<td>3.0</td>
<td>1.25</td>
<td>1.00</td>
<td>0.0</td>
<td>3.0</td>
</tr>
<tr>
<td>AELO</td>
<td>132.5</td>
<td>97.5</td>
<td>1041</td>
<td>1598</td>
<td>1342.7</td>
<td>95.1</td>
<td>1041</td>
<td>1640</td>
</tr>
<tr>
<td>AAge</td>
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<td>6.25</td>
<td>1.0</td>
<td>19.0</td>
<td>12.49</td>
<td>5.98</td>
<td>1.0</td>
<td>19.0</td>
</tr>
<tr>
<td>ADP</td>
<td>1.24</td>
<td>1.00</td>
<td>0.0</td>
<td>3.0</td>
<td>1.23</td>
<td>1.00</td>
<td>0.0</td>
<td>3.0</td>
</tr>
<tr>
<td>SELO</td>
<td>102.9</td>
<td>12.1</td>
<td>72.8</td>
<td>131.7</td>
<td>1029</td>
<td>12.1</td>
<td>72.8</td>
<td>131.7</td>
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</table>

Table 3-2. Average 2014 Single Game Ratings for MLS Team Markets

<table>
<thead>
<tr>
<th>Team (Market)</th>
<th>Market (City)</th>
<th>Rating</th>
<th>City Pop.</th>
<th>City Viewers</th>
<th>MSA Pop.</th>
<th>MSA Viewers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seattle Sounders</td>
<td>Seattle</td>
<td>2.443</td>
<td>637,850</td>
<td>15,583</td>
<td>3,671,478</td>
<td>89,694</td>
</tr>
<tr>
<td>Real Salt Lake</td>
<td>Salt Lake City</td>
<td>1.671</td>
<td>189,267</td>
<td>3,163</td>
<td>1,153,340</td>
<td>19,272</td>
</tr>
<tr>
<td>Portland Timbers</td>
<td>Portland</td>
<td>1.399</td>
<td>602,568</td>
<td>8,430</td>
<td>2,348,247</td>
<td>32,852</td>
</tr>
<tr>
<td>Sporting Kansas City</td>
<td>Kansas City</td>
<td>1.235</td>
<td>465,005</td>
<td>5,743</td>
<td>2,071,133</td>
<td>25,578</td>
</tr>
<tr>
<td>Chivas USA</td>
<td>Los Angeles</td>
<td>0.526</td>
<td>3,862,210</td>
<td>20,315</td>
<td>13,262,220</td>
<td>69,759</td>
</tr>
<tr>
<td>Philadelphia Union</td>
<td>Philadelphia</td>
<td>0.382</td>
<td>1,546,920</td>
<td>5,909</td>
<td>6,051,170</td>
<td>23,115</td>
</tr>
<tr>
<td>DC United</td>
<td>Washington, DC</td>
<td>0.361</td>
<td>633,736</td>
<td>2,288</td>
<td>6,033,737</td>
<td>21,782</td>
</tr>
<tr>
<td>Chicago Fire</td>
<td>Chicago</td>
<td>0.311</td>
<td>2,712,608</td>
<td>8,436</td>
<td>9,554,598</td>
<td>29,715</td>
</tr>
<tr>
<td>Colorado Rapids</td>
<td>Denver</td>
<td>0.236</td>
<td>633,777</td>
<td>1,496</td>
<td>2,754,258</td>
<td>6,500</td>
</tr>
<tr>
<td>New York Red Bulls</td>
<td>New York</td>
<td>0.201</td>
<td>8,354,889</td>
<td>16,793</td>
<td>20,092,883</td>
<td>40,387</td>
</tr>
<tr>
<td>Los Angeles Galaxy</td>
<td>Los Angeles</td>
<td>0.198</td>
<td>3,862,210</td>
<td>7,647</td>
<td>13,262,220</td>
<td>26,529</td>
</tr>
<tr>
<td>San Jose Earthquakes</td>
<td>San Jose-SF-Oak</td>
<td>0.198</td>
<td>986,320</td>
<td>1,953</td>
<td>6,546,932</td>
<td>12,963</td>
</tr>
<tr>
<td>Houston Dynamo</td>
<td>Houston</td>
<td>0.137</td>
<td>2,167,988</td>
<td>2,970</td>
<td>6,490,180</td>
<td>8,892</td>
</tr>
<tr>
<td>FC Dallas</td>
<td>Dallas</td>
<td>0.132</td>
<td>1,240,985</td>
<td>1,638</td>
<td>6,954,330</td>
<td>9,180</td>
</tr>
<tr>
<td>New England Revolution</td>
<td>Boston-Providence</td>
<td>0.116</td>
<td>639,594</td>
<td>742</td>
<td>6,341,528</td>
<td>7,356</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>---</strong></td>
<td><strong>0.636</strong></td>
<td><strong>1,902,395</strong></td>
<td><strong>6,874</strong></td>
<td><strong>7,105,884</strong></td>
<td><strong>28,238</strong></td>
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</table>

Average ratings measured as percentage of local market watching a game, on average, for the duration of the game. A rating of 1.0 implies 1% of the market. MSA and City population refers to 2014 estimates and come from the U.S. Census (https://factfinder.census.gov). Implied viewers calculated as \( \left(\frac{\text{Rating}}{100}\right) \times (\text{MSA Pop.}) \). Combined MSA areas such as Providence (Boston) and San Francisco-Oakland (San Jose) are assumed to have similar ratings levels. These areas are included due to their proximity to the central market or stadium location of these teams. I note that, compared to other teams who have most games televised, very few Chivas USA and Dallas FC games were televised in 2014.
Table 3-3. Results of Home and Away Rating Regression Estimations

<table>
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<tr>
<th></th>
<th>ln(HomeMktRating)</th>
<th>ln(AwayMktRating)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WinProb</td>
<td>-0.01461</td>
<td>0.03619*</td>
</tr>
<tr>
<td></td>
<td>(0.01898)</td>
<td>(0.01950)</td>
</tr>
<tr>
<td>WinProb²</td>
<td>0.00012</td>
<td>-0.00040</td>
</tr>
<tr>
<td></td>
<td>(0.00020)</td>
<td>(0.00028)</td>
</tr>
<tr>
<td>HELO</td>
<td>0.01028***</td>
<td>0.00427</td>
</tr>
<tr>
<td></td>
<td>(0.00382)</td>
<td>(0.00380)</td>
</tr>
<tr>
<td>AELO</td>
<td>-0.00456</td>
<td>0.00937**</td>
</tr>
<tr>
<td></td>
<td>(0.00316)</td>
<td>(0.00440)</td>
</tr>
<tr>
<td>SELO</td>
<td>-0.00024</td>
<td>-0.00255</td>
</tr>
<tr>
<td></td>
<td>(0.00213)</td>
<td>(0.00241)</td>
</tr>
<tr>
<td>LagWinPct</td>
<td>-0.33341</td>
<td>-0.09470</td>
</tr>
<tr>
<td></td>
<td>(0.28476)</td>
<td>(0.32294)</td>
</tr>
<tr>
<td>HDP</td>
<td>0.04716</td>
<td>0.06413**</td>
</tr>
<tr>
<td></td>
<td>(0.03167)</td>
<td>(0.02830)</td>
</tr>
<tr>
<td>ADP</td>
<td>0.05910**</td>
<td>0.00198</td>
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<tr>
<td></td>
<td>(0.02494)</td>
<td>(0.03614)</td>
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<td>Rivalry</td>
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<tr>
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<td>(0.10159)</td>
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<tr>
<td>HAge</td>
<td>-0.19919***</td>
<td>0.00192</td>
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<td>(0.00483)</td>
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<tr>
<td>AAge</td>
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<td>-0.24848***</td>
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<tr>
<td></td>
<td>(0.00380)</td>
<td>(0.02375)</td>
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<tr>
<td>Cable</td>
<td>-0.39575***</td>
<td>-0.46076***</td>
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<tr>
<td></td>
<td>(0.06141)</td>
<td>(0.07524)</td>
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<tr>
<td>Primetime</td>
<td>0.00443</td>
<td>0.05322</td>
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<td>(0.07003)</td>
<td>(0.05775)</td>
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<td>StadiumAge</td>
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<td></td>
<td>(0.00462)</td>
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<td>Sellout</td>
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<td>(0.06905)</td>
<td>(0.07611)</td>
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<td>Income</td>
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<td>Cloudy</td>
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<td>(0.05193)</td>
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<tr>
<td>Precip</td>
<td>0.23001**</td>
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<td>Constant</td>
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<td>(2.20487)</td>
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N = 921
R² = 0.609

Home models include home team fixed effects, while Away models include away team fixed effects. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.
Table 3-4. Fixed Effects from Regression Estimations

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<td>2011</td>
<td>0.13888</td>
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<td>(0.10425)</td>
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<td>2012</td>
<td>0.39216***</td>
<td>0.62983***</td>
</tr>
<tr>
<td></td>
<td>(0.11137)</td>
<td>(0.11508)</td>
</tr>
<tr>
<td>2013</td>
<td>0.77342***</td>
<td>1.04609***</td>
</tr>
<tr>
<td></td>
<td>(0.11602)</td>
<td>(0.12192)</td>
</tr>
<tr>
<td>2014</td>
<td>0.85296***</td>
<td>1.30502***</td>
</tr>
<tr>
<td></td>
<td>(0.12964)</td>
<td>(0.13114)</td>
</tr>
<tr>
<td>April</td>
<td>-0.26511***</td>
<td>-0.05713</td>
</tr>
<tr>
<td></td>
<td>(0.09934)</td>
<td>(0.12123)</td>
</tr>
<tr>
<td>May</td>
<td>-0.20738**</td>
<td>-0.03518</td>
</tr>
<tr>
<td></td>
<td>(0.09262)</td>
<td>(0.11098)</td>
</tr>
<tr>
<td>June</td>
<td>-0.19064*</td>
<td>-0.17558</td>
</tr>
<tr>
<td></td>
<td>(0.09856)</td>
<td>(0.11707)</td>
</tr>
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<td>July</td>
<td>-0.23421***</td>
<td>-0.09622</td>
</tr>
<tr>
<td></td>
<td>(0.09944)</td>
<td>(0.10742)</td>
</tr>
<tr>
<td>August</td>
<td>-0.24857**</td>
<td>-0.09818</td>
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<tr>
<td></td>
<td>(0.09784)</td>
<td>(0.11622)</td>
</tr>
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<td>September</td>
<td>-0.27996***</td>
<td>-0.07287</td>
</tr>
<tr>
<td></td>
<td>(0.09038)</td>
<td>(0.11234)</td>
</tr>
<tr>
<td>October</td>
<td>-0.45497****</td>
<td>-0.11714</td>
</tr>
<tr>
<td></td>
<td>(0.10026)</td>
<td>(0.10933)</td>
</tr>
<tr>
<td>Sunday</td>
<td>0.12196</td>
<td>0.29825***</td>
</tr>
<tr>
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<td>(0.07446)</td>
<td>(0.06745)</td>
</tr>
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<td>Monday</td>
<td>0.21423</td>
<td>0.35058</td>
</tr>
<tr>
<td></td>
<td>(0.19415)</td>
<td>(0.25287)</td>
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<td>0.81108***</td>
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<tr>
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<td>(0.19243)</td>
<td>(0.23100)</td>
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<td>(0.07907)</td>
<td>(0.08749)</td>
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<td>Thursday</td>
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<td>0.51729***</td>
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<td>(0.15338)</td>
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<td>Friday</td>
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<td>-0.05515</td>
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<tr>
<td></td>
<td>(0.12502)</td>
<td>(0.13779)</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.
Figure 3-1. Visualization of Monthly Effects for Attendance and Home Market Viewership
CHAPTER 4
SYNDICATE LEAGUE MODELING: CONJECTURAL VARIATIONS AND TALENT INVESTMENT

Introduction

The sports league modeling literature, especially since Fort and Quirk (1995), implicitly assumed professional sports leagues to be a form of business cartels. Therefore, most of the models have treated teams as individual firms, with the league itself as a collection of these firms. The critical problem that has been identified in this system is a disproportionate distribution of resources between league member teams, where team profitability is determined by the drawing potential of the market in which each team is located. In this sense, professional leagues in the U.S. have been defending their use of cross-subsidization policies, such as revenue sharing, asserting the role of these policies in the survival of the league. Specifically, it is argued that these policies are necessary for lower resource teams can compete with higher resource teams in larger markets. Otherwise the league would go out of business due to large market domination and lack of revenues for small market teams. This argument aligns with the idea of Rottenberg (1956) and Neale (1964), who posited that unpredictability in game outcomes, generated by equally distributed talent between contenders, is crucial to retain fan interest. This forms the basis of the UOH.

In spite of the appeal this idea may have, much of the sport economics literature has challenged legal and antitrust defenses related to the organization of sports leagues. The leagues’ argument implicitly assumes that sports fans place uncertainty as a primary factor driving interest and demand for play. However, empirical research has not found consistent evidence regarding Rottenberg’s UOH. Also, much of the economic literature modeling sports leagues has shown that cross-subsidization policies are unlikely to impact competitive balance, usually measured through the equality of winning percentages across competing teams.
In addition to lacking effects on competitive balance, this body of work has shown that many policies employed by the professional leagues reduce the incentive for teams to invest in playing talent. This could have two effects. First, it is likely that player pay is suppressed across the entire league. Secondly, it could produce a lower level of league quality in the long run. Particularly, much of the literature has found that sports fans also care about the absolute quality of team performance or playing talent as well as the relative quality (Brunggink & Eaton, 1996; Késenne, 2000; Marburger, 1997; Meehan, Nelson, & Richardson, 2007; Soebbing, 2008). That is, fans would be more interested in contests between high performance players (teams) rather than mediocre players (teams) so that not only the relative quality of a match but also the absolute quality of a match will affect the changes in demand. Therefore, prospective players would be discouraged to improve their potentials up to a certain point due to suppressed salaries and teams would also be discouraged for further development in talent due to investment disincentives, which eventually could put the league below the optimal overall quality level than otherwise. It is therefore the league structure and its policies that are under scrutiny in the literature as their implications are important in finding the optimal welfare status.

With a modeling focus largely within the cartel context, questions arise as to whether such implications hold in different league contexts or organizational structures. In particular, the single-entity structure of MLS shows a distinctive feature that differs from traditional cartel leagues: the league is treated as a single firm, with each team operated by its investors. This structure therefore drives inquiry into the effects of fully shared talent investment, and the way in which this impacts the choices of teams in hiring talent. In other words, the league is responsible of hiring overall playing talent in the league while its distribution is also centrally controlled through collective decisions made by all team operators. This structure could alleviate financial
burdens on each team’s talent investment by spreading the cost throughout the league. However, it is unclear what the implication of this unique feature is with respect to incentives for talent investment. Additionally, despite Késenne’s (2015) work on the single-entity status of professional sports leagues, no other studies have addressed the economics of the current MLS league structure. In this chapter, therefore, I investigate the implication of the syndicate league structure on talent investment, adopting the unique feature of MLS, sharing talent cost, and compare the result with cartel league outcomes.

League Structure of Major League Soccer

MLS differs from other major leagues in the U.S. in that it is operated as a Limited Liability Corporation (LLC), where investors share risks, liabilities, and profits of the entire league (Krasny, 2017). Additionally, according to each investors’ share in the pooled investments, some are allowed to oversee daily operations of a team (Francis & Zheng, 2010; Twomey & Monks, 2011). Specifically, the owner/investor retains a certain share of gate revenues while keeping all revenues from local broadcasting contracts and revenues from concessions and parking. On the other hand, MLS takes a certain share of gate revenues of its member teams and all revenues from national broadcasting contracts. However, as each team owner is also the member of the investors in the league, or serve as league organizers, team owners essentially take back what is shared from operations of the team and national broadcasting contracts. These aspects make the MLS league structure unique as compared to traditional cartel leagues. Therefore, a derivation of economic incentives faced by syndicate league investors – created by various revenue sources and the way they are shared – are a key contribution needed within the sports economics modeling literature.

On the cost side, each team owner/investor is responsible for hiring staff, any operational cost of stadium, and the construction of a new stadium (unless funded publicly). Additionally,
the team owner/investor is responsible for player salaries that are above the salary cap set by the
league. These players are called DPs, where the league only permits certain number of players
for each team. Costs at the league level are considerably higher than other leagues, as MLS is
responsible for all the player salaries – as the league holds the rights and contracts for all players
– and organizational operation costs. MLS then allocates budgets (salary cap) for hiring talent so
that each team are allowed to have equivalent level of talents. Therefore, a different investment
and operations cost approach is needed to derive economic implications of the MLS league
structure, as compared with other leagues.

Specifically, I first assume that MLS adopts a form of pooled revenue sharing. Although
sharing of pooled revenue depends on the share of investment of each investors/owners, I assume
that each team owner receives the same proportion of pooled revenue for simplicity of the model
and due to limited information regarding the true shared proportion in MLS. Secondly, unlike
other major leagues, player allocation is centrally controlled by the league and player costs are
transferred to the league, except the salary of DPs if a team decides to hire any. This system of
player contracts resembles the previous reserve clause of MLB, where property rights are simply
transferred from team owners to the league while players’ choices are stripped away. That is,
autonomy among players and individual free market investment choices are absent. Players are
allocated by the league through what is known as the Allocation Ranking to guarantee teams in
need are with priority (MLSSoccer.com, 2018). Lastly, it is somewhat unclear as to whether MLS
operates in a fixed or open talent market, and therefore different conjectural variations should be
considered. The supply of soccer players is somewhat unlimited since it is not limited to the U.S.
and MLS itself. However, difference in the regular season of MLS and European leagues may
inhibit many player transfers. Moreover, less competitive salary offers compared to European
leagues and explicit limitations on international players (184 slots in total, 8 per team) may deter an inflow of promising world-class athletes.

**Theoretical Model of the Syndicate League**

**Profit Functions of Syndicate and Cartel league**

I begin by defining the revenue function as in past work (El-Hodiri & Quirk, 1971; Szymanski, 2004; Szymanski & Késenne, 2004). Let team $i$’s revenue be a function of win percentage. That is, the revenue function of team $i$ is:

$$R_i(w_i(t_i, t_j); m_i)$$

where $\frac{\partial R_i}{\partial w_i} > 0$ and $\frac{\partial^2 R_i}{\partial^2 w_i} < 0$. This ensures a decreasing marginal product of winning, making the revenue function concave. Revenues are also a function of market size, $m_i$, and $w_i(t_i, t_j)$ is team $i$’s share of winning percentage for matches between team $i$ and team $j$.

Secondly, the relationship between winning percentage and talent can be explained by the Contest Success Function (CSF) used in previous work (Fort & Quirk, 1995). That is, winning percentage is a ratio of talent level such that

$$w_i = \frac{t_i}{T}$$

where $T = \sum_{i=1}^{n} t_i$, the total talent level in the league. As in the previous literature, winning percentage is a concave function of talent where $\frac{\partial w_i}{\partial t_i} > 0$ and $\frac{\partial^2 w_i}{\partial^2 t_i} < 0$ while adding up constraint, $\frac{\partial w_i}{\partial t_i} = -\sum_{j \neq i}^{n} \frac{\partial w_j}{\partial t_i}$, for winning percent summing to unity.

Next, in order to set up a comparison between the cartel and syndicate league, the profit function of both leagues should be defined. Since the revenue structure in MLS resembles the features of pooled revenue sharing, further specification will be based on the work of Chang and
Sanders (2007) and Easton and Rockerbie (2005). In the standard cartel model, the profit of team \( i \) is as follows,

\[
\pi_i^C = \alpha R_i (w_i(t_i, t_j); m_i) + \frac{1}{n} (1 - \alpha) \left[ \sum_{i} R_i (w_i(t_i, t_j); m_i) \right] - ct_i
\]

where \( \alpha \) is the percentage that is shared \((0 \leq \alpha \leq 1)\), \( n \) is the total number of teams, \( c \) is the cost of each unit of talent, and \( ct_i \) is the total talent cost for team \( i \). The profit function here illustrates that team \( i \) keeps \( \alpha \) percent of their own revenues, while sharing \((1 - \alpha)\) split across \( n \) teams.

In the case of MLS, the one critical difference is in player cost. Since the league is responsible for splitting total talent costs, the profit function is rearranged by moving the cost within the sharing structure. Then, the profit of team \( i \) in syndicate league like MLS is then as follows,

\[
\pi_i^S = \alpha R_i (w_i(t_i, t_j); m_i) + \frac{1}{n} \left[ (1 - \alpha) \sum_{i} R_i (w_i(t_i, t_j); m_i) - c \sum_{i} t_i \right]
\]

The term \( c \sum_{i} t_i \) is then the total cost of talent within the league. The difference from the cartel league profit function is that the cost is now shared amongst \( n \) number of teams.

From these profit functions, I first evaluate differences in talent investment for syndicate and cartel leagues. Assuming a two team league for the illustration, the profit functions of team 1 for the syndicate league and cartel league, respectively, are as follows:
(1) \( \pi^S_1 = \alpha R_1(w_1(t_1, t_2)) + \frac{1}{2} [(1 - \alpha)R_1(w_1(t_1, t_2)) + (1 - \alpha)R_2(w_2(t_1, t_2)) - c(t_1 + t_2)] \)

(2) \( \pi^C_1 = \alpha R_1(w_1(t_1, t_2)) + \frac{1}{2} (1 - \alpha) [R_1(w_1(t_1, t_2)) + R_2(w_2(t_1, t_2))] - ct_1 \)

where \( \frac{\partial w_1}{\partial t_1} = -\frac{\partial w_2}{\partial t_1} \) since \( w_1 + w_2 = 1 \) for the adding-up constraint. Then, taking first order condition with respect to talent investment of team 1 for both leagues, I get the following.

(3) \( \frac{\partial \pi^S_1}{\partial t_1} = \alpha \frac{\partial R_1}{\partial w_1} \frac{\partial w_1}{\partial t_1} + \frac{1}{2} (1 - \alpha) \left[ \frac{\partial R_1}{\partial w_1} \frac{\partial w_1}{\partial t_1} + \frac{\partial R_2}{\partial w_2} \frac{\partial w_2}{\partial t_1} \right] - \frac{1}{2} c \left( 1 + \frac{dt_2}{dt_1} \right) = 0 \)

(4) \( \frac{\partial \pi^C_1}{\partial t_1} = \alpha \frac{\partial R_1}{\partial w_1} \frac{\partial w_1}{\partial t_1} + \frac{1}{2} (1 - \alpha) \left[ \frac{\partial R_1}{\partial w_1} \frac{\partial w_1}{\partial t_1} + \frac{\partial R_2}{\partial w_2} \frac{\partial w_2}{\partial t_1} \right] - c = 0 \)

Intuitively, assuming equal levels of marginal revenue from talent investment for both leagues, the difference in these two models is the marginal cost, where syndicate leagues have \( MC_S = \frac{1}{2} c \left( 1 + \frac{dt_2}{dt_1} \right) \) while cartel leagues have \( MC_C = c \).

For further illustration of the model, I now assume that revenue function of each team is solely based on the share of talent, so that \( R_1(w_1(t_1, t_2)) = \frac{t_1}{t_1 + t_2} \) and \( R_2(w_2(t_1, t_2)) = \frac{t_2}{t_1 + t_2} \).

Then, the marginal revenue of team 1 is

\[
\frac{\partial R_1}{\partial w_1} \frac{\partial w_1}{\partial t_1} = \frac{t_1 + t_2 - t_1 \left( 1 + \frac{dt_2}{dt_1} \right)}{(t_1 + t_2)^2} = \frac{t_1}{t_1 + t_2} \left( 1 + \frac{dt_2}{dt_1} \right)
\]

Following previous work, I assume that \( t_1 + t_2 = 1 \) from the normalization to unity of the total league talent level (Fort & Quirk, 1995; Szymanski, 2004). Hence, this can be rewritten as

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\[
\frac{\partial R_1}{\partial w_1} \frac{\partial w_1}{\partial t_1} = 1 - t_1 \left( 1 + \frac{dt_2}{dt_1} \right)
\]

Then, the marginal profit function both league can be rewritten as

\begin{align*}
(5) \quad \frac{\partial \pi^s}{\partial t_1} &= \alpha \left( 1 - t_1 \left( 1 + \frac{dt_2}{dt_1} \right) \right) - \frac{1}{2} c \left( 1 + \frac{dt_2}{dt_1} \right) = 0 \\
(6) \quad \frac{\partial \pi^c}{\partial t_1} &= \alpha \left( 1 - t_1 \left( 1 + \frac{dt_2}{dt_1} \right) \right) - c = 0
\end{align*}

Since \( \frac{\partial R_2}{\partial w_2} = - \frac{\partial R_1}{\partial w_1} \) from the adding up constraint. Assuming equal market to allow equal marginal revenues for both teams, the shared portion disappears.

**Talent Supply and Conjectures**

As mentioned above, MLS is in between a fixed or perfectly open market due to several features. This may also be true for other leagues where there exists a potential global labor pool, but structural features and transactions costs may limit the inflow of international labor pool. As such, these professional leagues would have limited access to the open market, characterizing the league as *semi-open* or *semi-fixed.* That is, talent acquisition is not a zero-sum game, but there are losses that may exist for other teams who fail to acquire talent. In this context, conjectures with respect to the response of teams to a change in talent for another team should be approached differently than in the conventional *Walrasian conjecture* \( \left( \frac{dt_2}{dt_1} = -1 \right) \) or more recent *Nash conjecture* \( \left( \frac{dt_2}{dt_1} = 0 \right) \) suggested by Szymanski (2004).
From equation (5) and (6), the optimal level of talent for each team in each league then can be rewritten as:

\[
(7) \quad t^{*}_{1S} = \frac{1}{(1 + \frac{dt_2}{dt_1})} - \left(\frac{1}{2}\right) \frac{c}{\alpha}
\]

\[
(8) \quad t^{*}_{1C} = \frac{1}{(1 + \frac{dt_2}{dt_1})} - \frac{c}{\alpha(1 + \frac{dt_2}{dt_1})}
\]

where \( t^{*}_{1S} \) is the optimal level of talent for team 1 in a syndicate league and \( t^{*}_{1C} \) is the optimal level of talent for team 1 in a cartel league. Intuitively, the optimal level of talent in the syndicate league depends on the number of teams in the league (2 in this case), while it depends on the talent acquisition conjecture for the cartel league.

First, assuming that talent acquisition of one team does lead to some loss for the others, the talent choice response indicator of team 2 for increase in talent for team 1 is between 0 and -1. For purposes here, it is assumed that \( \frac{dt_2}{dt_1} = -\frac{1}{2} \). This means that when team 1 increases its talent by one unit, team 2 loses a one-half unit share. I refer this assumption as semi-fixed conjecture where acquisition of talent results in a partial loss of labor share for other teams. Applying this assumption to equation (7) and (8), the optimal talent level of team 1 for both leagues are

\[
t^{*}_{1S} = 2 - \left(\frac{1}{2}\right) \frac{c}{\alpha} \quad \text{and} \quad t^{*}_{1C} = 2 - (2) \frac{c}{\alpha}
\]

For any \( \alpha \leq 1 \) under semi-fixed labor market, the talent level of team 1 in the syndicate league will be higher than that of cartel league. Similar results can be found when talent choices are
independent between teams \(\frac{dt_2}{dt_1} = 0\), where \(t_{1S}^* = 1 - \left(\frac{1}{2}\right) \frac{c}{\alpha}\) and \(t_{1C}^* = 1 - \frac{c}{\alpha}\). Therefore, it can be inferred that if talent acquisition for one team has no effect on others, teams in a syndicate leagues will seek to purchase a greater talent level compared to cartel leagues. These results at the individual team level come from the shared cost of talent across teams, reducing the cost for any one team to invest in talent.

Next, as the syndicate league operates as a single firm with centralized control of talent allocation, it is possible that one team’s change in talent would also lead to comparable talent changes for the other teams. This means that all other teams will increase the level of talent proportionally whenever one team increases talent. I refer this to as semi-syndicate conjecture. Nonetheless, even in this case, the first order condition shows a similar result of the semi-fixed conjecture. With this conjecture, I set \(\frac{dt_2}{dt_1} = \frac{1}{2}\), and the optimal talent level of team 1 for both leagues are now shown as

\[
t_{1S}^* = \frac{2}{3} - \left(\frac{1}{2}\right) \frac{c}{\alpha} \quad \text{and} \quad t_{1C}^* = \frac{2}{3} - \left(\frac{2}{3}\right) \frac{c}{\alpha}
\]

As shown here, talent level of team 1 in the syndicate league is still slightly higher than that of cartel league. By providing other teams with a proportional increase in talent in the face of talent additions by one team, it seems that talent level investment incentive remains higher in syndicate leagues compared to that of cartel leagues.

In a more extreme case, it is also possible that the syndicate league would perfectly compensate talent changes for every team in the league. This means that one unit increase in one team will result in equal unit increase in the other team. I refer this as perfect-syndicate
conjecture, where $\frac{dt_2}{dt_1} = 1$. Interestingly, applying this assumption, the optimal level of talent in both leagues converges. That is, $t_{1S}^* = \frac{1}{2} (1 - \frac{c}{\alpha}) = t_{1C}^*$, so that there is no difference in talent choice for team 1 in the syndicate or cartel league. In this scenario, the distinction between the syndicate and cartel sports leagues becomes moot, and they may be treated similarly from a policy standpoint. Nevertheless, the necessary condition for this conjecture to hold in any league is that there exist players with an equivalent level of playing talent. Moreover, this conjecture is more appropriate in the case of central control over talent allocation so that it is difficult to apply in cartel league context.

The changes in the talent level of team 1 with respect to changes in level of revenue sharing, $\alpha$, are then shown in Figure 4-1 and 4-2 assuming fixed cost of talent. First, under semi-fixed conjecture (Figure 4-1), it shows that as the proportion of revenue sharing increases, the level of talent employed by the team 1 increases under both league structure, while the magnitude of increase will be higher for cartel leagues. However, the absolute level of talent hired by team 1 in the syndicate league is likely to be higher. Similarly for the semi-fixed conjecture, the Figure 4-2 shows that level of talent employed by the team 1 increases under both league structure, while the magnitude of the increase will be larger for the cartel leagues as the level of revenue sharing increases. The level of talent employed by team 1 is higher for the syndicate league team than cartel league team. It is then possible that the difference is due to the shared cost of talent. Syndicate league teams are more likely to invest in talent when the cost of talent is transferred to the league, while an increase in revenue sharing increases the level of talent hired by both teams but at a decreasing rate.
Conclusion

In this chapter, I first attempted to model syndicate league based on single-entity structure of MLS and find the difference in talent investment expectations for both the syndicate and cartel league structure. As Winfree (2015) noted, there are still unexplored areas in the discussion of conjectural variations in sports league modeling. Here, I consider different conjectures on talent investment in which talent acquisition is explained by changes in the share of total talent. These conjectures are most useful in a setting where talent supply elasticity is somewhat between perfectly fixed or open. I therefore introduce variations of talent conjectures to incorporate different dynamics of the professional sport labor pool, and reinforce the conventional conjectural discussion in a broader landscape of league design.

Using these conjectures in a pooled revenue sharing league model, the talent choices of teams in the syndicate and cartel leagues are assumed to be based on the loss or gain in talent share by other league teams. However, assuming no market size differences and constant talent unit costs, it seems that level of talent hired under a syndicate league would be higher than a cartel league whether a gain or loss occurs for the other member teams when the marginal talent level increases for one team. The incentive to increase talent, however, becomes equivalent for the syndicate and cartel league when other teams respond with equivalent talent gains.

Assuming the semi-syndicate conjecture is the most suitable assumption for MLS, the work here shows that increases in sharing of revenue will create talent investment disincentives for team owners due to revenue sharing decreasing the value of additional talent (winning). This is consistent with previous work (Fort & Quirk, 1995; Chang & Sanders, 2009). However, as the level of talent hired by the syndicate league team is higher than the cartel league team, it shows that there are possible increases to talent investment incentives by sharing the cost of talent even under revenue sharing, as compared with the cartel league. There is then evidence of advantages
for a syndicate league over cartel leagues from an individual team owner welfare perspective. Here, the financial burden is reduced for each team through sharing total talent costs, leading to an incentive to have a greater level of talent employed by any individual team.

However, from the perspectives of fan and player welfare, greater incentives to hire talent at the individual team level does not guarantee increased playing quality of the league. As shown in past work (Twomey & Monks, 2011), salary suppression in MLS is larger than other major leagues in the U.S., providing evidence of greater monopsonistic power over players, which implies that the overall quality of the league may be lower (Késenne, 2015). Lower salary for the players then indicates that MLS might be attracting more relatively lower quality players, preventing high performing players to enter the league, which eventually would not help improve the overall quality of the league. As a result, it might be that fans are still left with a lower quality league in comparison to cartel leagues or a free market league as Késenne (2015) noted, particularly with substantial competition for soccer talent in other countries. This may then cast questions on the necessity of the league syndication over cartel league in respect to quality, while the obvious advantage of the structure would be for the team owners regarding to directly suppress talent investment allowances and reduce overall salaries.

Although the promotion of competitive balance might be appealing for the league from the perspective of legal protections and financial stability, the empirical work in previous chapters has shown that fans are more concerned with absolute quality. Without changes to talent investment incentives and league policies that promote increases in absolute quality of the league, MLS may experience growth difficulties going forward. This is likely the impetus for the DP rule, allowing individual teams to make these investments. Less stringent restrictions on DPs
then may allow individual owners to attract not only more high profile players, but also other quality players, which could help improve the overall quality of the league.

Acknowledging these implications, the next question is then to understand what would happen in the case of league with more than two teams. As sharing the cost of players may create greater investment incentives under a pooled revenue sharing structure, the total talent investment would likely depend on the total number of teams in the league, or the league-level incentives for expansion. It would be worth further inquiry into how potential expansion teams with revenue above or below the league average would affect the league’s aggregate talent cost. Additionally, although the model in this work assumes talent cost are constant for all teams, it would be useful to exhibit the effects of market size heterogeneity in revenues or costs. MLS allocates equivalent maximum player budgets for each team, although teams are not required to fill all their roster. Therefore, even in the current single-entity structure, each team will have different levels of total talent investment. Furthermore, the inclusion of a separate cost factor of DPs, which is not shared, would extend the discussion of heterogeneous investment choices of team owners. Lastly, incorporating the differential effects of relative and absolute quality within the revenue function would enhance the understanding of incentives faced by teams with a mix of shared and unshared costs. Increases in talent investment would likely result in greater total compensation for players, therefore increasing the absolute quality of the league by attracting more quality players. As exhibited in Chapters 2 and 3, this also has a crucial influence on MLS fan demand. Theoretical consideration of talent investment incentives with respect to relative and absolute quality is therefore important from a policy perspective. Expanding this model by integrating both relative and absolute quality will be useful to more precisely evaluate on differences that may exist in heterogeneous investment choices (Salaga, Ostfield, & Winfree,
2014). Addressing these questions would enrich our understanding of underlying economics of various league designs and its utility for both new and growing professional sports leagues.
Figure 4-1. Changes in talent level (*semi-fixed* conjecture)

Figure 4-2. Changes in talent level (*semi-syndicate* conjecture)
CHAPTER 5
GENERAL DISCUSSION

Consumer theory in economics focuses upon understanding individuals’ decisions, limited by budget constraints, related to his or her consumption choices. Satisfaction (or utility) resulting from consumption of some good is different for each consumer, as their preferences are heterogeneous. Individual preferences are also not static, as they may evolve across time or as individual income changes. In this sense, demand studies are imperative to understand evolving consumer preferences to ensure businesses and organizations offer what their consumers want. Although there are peculiarities of the professional sports business that distinguish it from other industries, the underlying nature of sports fan consumption can be useful in understanding behavior both in sport and beyond.

For many years, however, sports leagues have been using similar assumptions about fan preferences to justify the use of cooperative policies and maximize league welfare at the cost of fan and player welfare. That is, leagues argue that uncertainty is what sports fans desire, and therefore instituting league balance is necessary over other considerations, aligned with ideas posited by Rottenberg (1956) and Neale (1964). While the impact of this foundational work is undeniable, the way fans consume professional sports has been and is still evolving. As the medium for consuming sports evolves, more fans with diverse interests and preferences have access to consumption. Therefore, despite the value of guiding work related to competitive balance and uncertainty of outcome, empirical work should ensure that a broader coverage of these topics is undertaken across leagues and across time. In particular, as Fort (2017) noted, the academic literature has challenged Rottenberg’s UOH across various leagues, and therefore requires substantial evidence across various contexts to guide proper policy implementation.
Furthermore, there has been a continuous effort to theorize professional sports leagues in formal economic models. In particular, regarding the use of cooperative policies of professional sports leagues, the majority of sports economists have refuted the league-purported competitive balance effects of these policies. In general, there exists strong evidence of Rottenberg’s IP, where cross-subsidization would not result in convergence to a perfect balance as claimed by the sports leagues.

MLS is then a good representation of syndicate professional leagues, in which the league acts as a single firm. This U.S. league has received increasing academic interest as it has expanded in recent years, with work primarily focused on fan demand. Aligned with these trends, this dissertation attempted to identify determinants of demand and their effects on fan behavior, with particular interest in relative and absolute quality. Furthermore, I made small adjustments to common sports league models to evaluate changes to talent investment when moving to the syndicate league structure.

**Summary of Findings and Discussion**

As with prior work on sports demand, the work here also used Rottenberg’s UOH to guide inquiry into MLS attendance and viewership demand. The central finding of the empirical work presented here was that demand for MLS was found to be unaffected by uncertainty of outcome. Additionally, I important influences of absolute quality and superstar presence on fan demand for MLS both at the stadium and in game broadcasts. While the closeness of a match was not a central consideration for demand for MLS, higher team quality and number of superstars played a pivotal role in attracting fans to the stadium and television.

For attendance demand, I find evidence in reverse of the predictions of Rottenberg, in which attendance was maximized where the game outcomes were more predictable. In other words, increases in attendance were observed whenever the home or away team had greater
chance of winning. On the contrary, no evidence was found in viewership demand that related to uncertainty over the game outcome. Therefore, the assumption of fan preferences in favor of close matches does not seem to apply in the MLS context. This finding is therefore aligned with the loss aversion hypothesis developed by Coates, Humphreys, and Zhou (2014): MLS fans have preferences against risks or uncertain outcomes.

Furthermore, the previous track of record for each team significantly impacted changes in MLS fan behavior, where teams with greater success in competition enjoyed increased demand. That is, home teams with higher Elo ratings had greater appeal for more home fans to come out to the stadium, while away teams with higher Elo ratings also attracted more home fans, generating a visiting team quality externality. Additionally, superstar effects were present. Additional DPs on both the home and away teams triggered increases in attendance demand. However, the increase in ratings was observed only for the presence of an opponent teams’ DP, confirming the presence of a superstar externality noted in previous literature (Berri & Schmidt, 2006; DeSchriver, 2007; Hausman & Leonard, 1997). Combining these findings, I exhibit substantial evidence that sports fans care not necessarily about relative quality, but also about the absolute or aggregate quality of sporting contests in MLS (Késenne, 2000; Meehan, Nelson, & Richardson, 2007; Soebbing, 2008).

Since both the work in attendance and viewership demand was conducted in the same markets and across the same time period, investigation into the relationship between live game attendees and television audience revealed strong evidence of substitution between these types of consumption. Whenever home games were sold out, I find that the excessive demand beyond stadium capacity was captured through live game broadcasting. Additionally, when the weather was subpar, a portion of attendance demand was shifted to viewership demand. The most
interesting finding was a shift of viewership to attendance as the season progressed. This result provides evidence that risk preferences of MLS fans are important in their consumption choices. In particular, fans tend to avoid uncertainty in expected outcomes at the beginning of the season, presumably due to a lack of information about team performance quality in the current year. However, as season progresses and information about team quality is revealed, fans are more likely to attend games at the stadium instead of watching on television. The unpredictability of playoff advancement and league standing reduces as the season approaches to the end, which enables fans to avoid possibility of experiencing unexpected outcomes when attending games, which have a substantially higher cost of consumption than watching on television. Such behavior is consistent with loss aversion of sports fans (Coates, Humphreys, & Zhou, 2014), where availability of more information about expected outcomes may lower the perceived attendance risk or opportunity cost (e.g., reserve utility) of attending the game.

As the empirical work here has found the importance of the absolute quality of teams and players, subsequent questions arise as to whether the current structure of the MLS is suitable in satiating the desire of their fans, or whether this structure is necessary to achieve the current league results. Since the centralized control of player allocation may ensure that no single team owner will greatly overspend others and substantially deteriorate balance within the league, I introduce less extreme talent conjectures than the Walrasian or Nash conjectures for theoretical modeling of a syndicate league like MLS. This portion of the study shows that the level of talent hired in a syndicate league like MLS would be greater than the cartel league for both the semi-fixed and semi-syndicate conjectures, ceteris paribus. This seems to be mainly due to the sharing of player costs, where individual teams take on the full cost of talent in cartel leagues, syndicate leagues reduce the cost of any individual decision to increase talent investment. Additionally,
under these conjectures, the relative change in total talent investment across the league structures depends on the level of sharing. Nevertheless, increased individual team incentives to increase the level of playing talent does not necessarily imply an increase in playing quality for the league under the current conditions. In particular, it is possible that the model presented here shows incentives for each team to invest more in talent, while the talent budget restrictions in MLS would prevent this. That is, the quality of the league will remain the same unless league policy on player allocation or allowances changes. Additionally, since MLS is the sole domestic buyer of labor, the league will have increased monopsony over its players leading suppression in salaries. In turn, MLS likely attracts lower quality players in the face of competition from international soccer leagues who might be willing to pay more for quality players. This implies that the current structure of MLS is more geared towards maximizing individual team owner welfare by effectively reducing the costs of operation while leaving consumers with sub-optimal product and providing players with sub-optimal career options.

As a whole, the work here evaluates the utility of the current structure of MLS promoting equal distribution of playing talent amongst teams. It may have been a reasonable choice for MLS to adopt single-entity structure as the league began to ensure stability, learning from the previous failure of NASL. However, as time passed and as MLS exerts greater influence within the U.S. professional sports market, it may be time for MLS to reevaluate its standing and reconsider future strategy. As shown under both of the semi-fixed and semi-syndicate conjectures of the model, teams in MLS likely to have increased talent investment incentives, while also suppressing the salary through shared talent costs, highlighting the importance of considering how this affects the absolute quality of this league relative to one under a cartel structure or even free market leagues. Nonetheless, as the empirical work indicates that there are preferences for
higher team performance at the local level and quality playing talent across the league as a whole, a reconsideration of the current structure and policies of MLS in terms of attracting better quality players seems worthwhile. In other words, rather than aiming to provide an equal distribution of resources for competitive balance and putting greater restrictions on player investment, incentivizing each team operator to win more games, encouraging development of playing quality, and attracting higher quality players through allowing more talent investment may ultimately be beneficial for the league to continue its seemingly growing fan interest.

### Limitations and Future Directions

The empirical analysis in this work on demand for MLS extends the discussion of the role of playing quality for both attendance and viewership. Of course, despite the use of betting information as a proxy of relative quality, there still exist possibility of difference in actual fans’ perception of closeness of competing teams. It is possible that home fans may exhibit a biased evaluation of home team performance, in which they overestimate the probability of winning relative to more efficient betting expectations. Integrating this into the estimation of relative quality then could yield more accurate result on fan behavior (Nalbantis, Pawlowski, & Coates, 2017). Additionally, an advantage that ratings data has is the ability to capture the variation in viewership during a game. However, due to limited data availability, only average ratings were used in the current study, prohibiting any investigation of fan responses due to changes in the game quality during gameplay. Previous work has shown that certain game characteristics may result in a loss of viewership, and extending this to MLS may be a fruitful way to measure interest in game uncertainty (Alavy, Gaskell, Leach, & Szymanski, 2010; Sung, Mills, & Tainsky, 2017; Xu, Sung, Tainsky, & Mondello, 2015).

With regard to the modeling of MLS, one limitation here is that I assume there is no market size difference for member teams. It is the general agreement that market size differences
affect the magnitude of revenue, which in turn affects the talent investment choices for teams (Chang & Sanders, 2009; Daly & Moore, 1981; Fort & Quirk, 1995; Késenne, 2000; 2004; Madden, 2011; 2013). It is also possible that accounting for market difference could affect talent choices in the model presented in the current study. Differences in revenue across markets could also affect the expansion strategy, where teams in large enough markets would be allowed to enter the league (Easton & Rockerbie, 2005).

Another limitation of the model is that the team revenue function is simplified such that it is solely dependent on the share of talent within the league (relative quality). That is, the relative share of talent is considered, ignoring the effects of higher total talent levels across the league (absolute quality). The revenue of a team is in fact a function of its demand, which is presumably a function of both relative and absolute quality, the latter of which was found to be quite important in the empirical results presented in this work. One possible way to account for the effect of total talent could be the inclusion of a DP variable within the model, given the key role of DPs shown in attendance and viewership demand. Constructing DP as a heterogeneous investment choice, an approach similar to Salaga, Ostfield, and Winfree’s (2014) work, could then yield useful insight on how talent investment choices would be made by individual teams. Additionally, the profitability of a marginal increase in DP would also provide useful insight in regards to interest in expanding investment allowances at the league level. If it is indeed the DPs who are bringing in significant revenue to MLS, more teams would be willing to invest to increase the number of DPs hired.

Overall, although limited, this work begins to theorize league structures outside the conventional cartel league model, possibly opening up a new discussion within the professional sports league modeling literature. Future work is encouraged to further develop implications of
different league designs in order to suggest avenues that may enhance collective welfare of leagues, individual team owners, players, and fans.
LIST OF REFERENCES


BIOGRAPHICAL SKETCH

Hojun Sung received his Ph.D. from the Department of Tourism, Recreation, and Sport Management within College of Health and Human Performance at University of Florida in the August 2018, as well as a graduate minor in statistics. He also holds master’s degree from the University of Illinois. Most of his research works with large databases – including public attendance data, Nielsen ratings data, and private ticketing data – to test various models of sports consumer behavior and demand for sports. He has experience publishing papers in top sport management and sports economics journals, as well as various conference presentation experiences in North American Society for Sport Management and European Association for Sport Management conferences.

Dr. Sung’s research has centrally focused upon consumer behavior, demand for sport, and the industrial organization of professional sports leagues. His research has applied rigorous quantitative and econometric approaches to test these economic theories to derive comprehensive and impartial managerial or policy implications and understand the interrelationship between sports league structures and fan behavior.

From the teaching perspective, Dr. Sung has been a teaching assistant and grader for the online undergraduate and graduate level sport finance courses at the University of Florida since 2015. Additionally, he was the instructor for the department’s on-campus undergraduate sport finance in the 2018 Spring semester. Prior to the time at Florida, he served as an assistant for foundations of sport management at the University of Illinois for two semesters and gave multiple guest lectures in foundations of sport management related to sport law and sport finance/economics.