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FAN RESPONSE TO LEAGUE PLAYOFF STRUCTURE AND CONSECUTIVE SEASON COMPETITIVE BALANCE IN PROFESSIONAL SPORTS

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A Dissertation Presented

By

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ABSTRACT

FAN RESPONSE TO LEAGUE PLAYOFF STRUCTURE AND CONSECUTIVE SEASON COMPETITIVE BALANCE IN PROFESSIONAL SPORTS

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Competitive balance (the level of equality of playing talent across teams) is presumed to be a necessary element for league success due to the unique inter-dependent economic nature of professional sports which requires teams to have financially healthy rivals in order to field games (Rottenberg 1956). Underlying this notion is the uncertainty of outcome hypothesis, which suggests that a fan's interest in professional sports is dependent on various levels of uncertainty of outcome: individual game uncertainty (who will win the game), individual season uncertainty (who will win the championship), and consecutive season uncertainty (does the same team win the championship every year) (Cairns 1987). Although there is an expanding body of literature that empirically tests the uncertainty of outcome hypothesis, most of it focuses on attendance responses to within-game or within-season measures of competitive balance. In addition, nearly all previous studies focus on regular season outcomes only and completely ignore the playoffs (Longley and Lacey 2012). Filling in a notable gap in the literature, this dissertation thus uses a new metric of competitive balance that relies on inter-seasonal measures of qualification for and advancement in the playoffs.

In addition to measuring fan response to this new measure of competitive balance that incorporates both playoff outcomes and consecutive season effects in a novel way, this dissertation also investigates the effects of league playoff rules on competitive balance. No previous study has analyzed how the number of teams that qualify for the playoffs affects fan interest in a league through competitive balance concerns. On the one hand, increasing the number of teams that qualify for the playoffs should increase fan interest by increasing the overall pool of teams that are competitive for a playoff spot. On the other hand, increasing the number of teams that qualify for the playoffs shifts the importance from the regular season to the playoffs, reducing fan interest in the regular season. This dissertation empirically investigates the issue of fan response (as measured by league-wide regular season attendance figures) to varying levels of inter-seasonal competitive balance as measured by the churn of playoff qualifying/advancing teams and as affected by league playoff structures that dictate the number of teams making the playoffs.

The results show that small changes in league playoff structure can significantly affect attendance. It is predicted that if Major League Baseball were to further increase the number of teams that make the playoffs from 10 to 12, the average attendance per game would increase by over 4,300 (about 14% of the current average). In the National Hockey League, a reduction in the number of teams that make the playoffs from 16 to 14 is expected to increase the average attendance per game by over 700 (about 4% of the current average). These results highlight the importance of including playoff considerations when investigating the uncertainty of outcome hypothesis as well as the value of competitive balance to sport league success.

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CHAPTER 1

INTRODUCTION

Competitive balance in sport has become a major research topic of interest in recent years. The early work (Rottenberg 1956; Neale 1964; El-Hodiri & Quirk 1971) effectively defined the unique inter-dependent economic nature of sport and how competitive balance, in theory, is essential for long-run profit maximization of a league and its member teams. More recent work has empirically investigated the levels of competitive balance in leagues over the years as well as any effects such balance (or lack thereof) has had on consumer behavior. Fort and Maxcy (2003) summarized these two distinct lines of recent competitive balance research as analysis of competitive balance (ACB) and uncertainty of outcome hypothesis (UOH) literature.

ACB research focuses on measuring the level of competitive balance in leagues and the effect on balance of league wide rule changes such as free agency. Cairns (1987) categorized competitive balance into three areas: individual game uncertainty (who will win the game), individual season uncertainty (who will win the championship), and consecutive season uncertainty (does the same team win the championship every year). Most research uses within-season uncertainty as the metric for competitive balance, but the precise measure of the level of balance takes many forms. Various measures of competitive balance include: standard deviation of win percentage (Quirk & Fort 1992), excess tail frequency of win percentage (Fort & Quirk 1995), Gini coefficients (Schmidt & Berri 2001), and the Herfindahl-Hirshman Index (Depken 1999).

In addition to the within-season research on competitive balance, several studies have looked to investigate long-term competitive balance under the premise that uncertainty of outcome across seasons is more important than within a given season. The reasoning is that fans are willing to continue to support and follow a team even if its prospects during the current season are dim as long as its potential for the next few seasons is sufficiently good. This represents a significant departure from the previous literature as within-season competitive balance only considers how evenly matched the teams are as a whole and not which specific teams are actually winning. Therefore, to assess the level of inter-seasonal competitive balance within leagues, new metrics are needed that measure effects across seasons such as the concentration of championships (Quirk and Fort 1992; Eckard 2001), cross-season correlation coefficients (Butler 1995; Lee and Fort 2008; Lee 2010) and Markov transitional probabilities (Hadley et. al. 2005; Krautmann and Hadly 2006).

Although ACB research has provided various measures of competitive balance in professional sports leagues over the years, as well as examples of policy changes that have affected competitive balance one way or the other, the research is fraught with uncertainties and contradictory findings. Overall, the field could benefit from the determination of a standard measure of competitive balance that is the most useful or important. However, determining usefulness or importance is a tricky situation. Zimbalist (2002) argues that “the best measure of competitive balance is the one to which the consumers show greatest sensitivity.” In Zimbalist’s view, competitive balance research should focus on investigating how the consumer responds to changes in the level of competitive balance (UOH research). He goes on to argue that many of the traditional means of measuring competitive balance by academics are inadequate because the fans do not experience game or season outcomes in that manner. As a result, this dissertation is rooted in UOH and seeks to define an appropriate competitive balance measure to which consumers show significant sensitivity.

Although there is an expanding body of uncertainty of outcome hypothesis (UOH) literature, most of it focuses on attendance responses to within-game measures of competitive balance (e.g. Peel and Thomas 1988, 1992; Knowles et. al. 1992) or within-season measures (e.g. Schmidt and Berri 2001; Meehan et. al. 2007). Filling in a notable gap in this literature, this dissertation thus proposes a new measure of competitive balance that relies on inter-season measures of qualification for and advancement in the playoffs. As pointed out in a recent paper by Longley and Lacey (2012), most previous competitive balance studies focus on regular season outcomes only and completely ignore the playoffs, which runs contrary to fundamental notions of how fans evaluate team success. For example, if a team finishes the regular season with the best record but then languishes in the playoffs, it will likely be considered an unsuccessful season. A recent example of this could be the 2001 Seattle Mariners which set the all-time regular season record for wins in Major League Baseball with 116 but lost in the 2nd round of the playoffs. Conversely, if a team just manages to make the playoffs but then ends up winning the championship, it will likely be considered a hugely successful season. In 2012 the New York Giants (National Football League) and Los Angeles Kings (National Hockey League) won their respective championships despite qualifying for the playoffs in their final game of the regular season. These examples highlight the importance of the playoffs and that such considerations, which are not found in most previous research, should form the basis of appropriate competitive balance measures. Therefore, this study proposes a playoff qualification/advancement churn variable that measures how frequently the same teams qualify for the playoffs each year and whether the same teams advance to each later round of the playoffs (including winning the championship).

In addition to measuring fan response to this new measure of competitive balance that incorporates both playoff outcomes and inter-season effects in a novel way, this study will also investigate the effects of league playoff rules on competitive balance for the first time. Longley and Lacey (2012) evaluated the effect of league playoff pooling structures on competitive balance, but no study has thus far investigated how the number of teams that qualify for the playoffs affects fan interest in a league through competitive balance concerns. Adding this effect of playoff structure to the study could be especially illuminating as within and across leagues, the number of teams that qualify for the playoffs each year has varied wildly.

Although there is a significant existing literature on competitive balance, much of it completely ignores the issue of the playoffs (both structure and outcomes) and how it affects the notion of the optimal level of competitive balance in sport leagues. Of the few studies that explicitly include competitive balance measures that relate to the playoffs, none consider inter-seasonal competitive balance or the effects of the number of playoff teams on this balance. The proposal for this paper is therefore to investigate the issue of fan response (as measured by league-wide attendance figures) to varying levels of inter-seasonal competitive balance as measured by the churn of playoff qualifying/advancing teams and as affected by league playoff structures that dictate the number of teams making the playoffs.

The remainder of the dissertation is structured as described below. Chapter 2 provides a review of the literature related to competitive balance in professional sports. Chapter 3 describes the conceptual theory forming the basis of this study and develops testable hypotheses. Chapter 4 describes the methodology for completing the investigation previously detailed. Chapter 5 summarizes the results of the empirical analysis used to test the hypotheses and offers a discussion of the important findings. Chapter 6 concludes with limitations, implications, and areas of future research.

CHAPTER 2

THEORETICAL FOUNDATIONS OF COMPETITIVE BALANCE

The notion of competitive balance and its importance to the health and viability of a professional sports league can be traced to Rottenberg's (1956) seminal article that essentially created the field of sport economics. Although Rottenberg specifically discusses Major League Baseball (MLB), his two principle arguments concerning competitive balance are applicable for all of the Big Four major professional sport leagues in the United States: MLB, the National Football League (NFL), the National Basketball Association (NBA), and the National Hockey League (NHL). First, Rottenberg asserts that some general level of competitive equality (i.e. all teams within a given league are composed of players with similar levels of talent) is necessary for a league to be financially successful. This argument is predicated on the unique economic inter-dependence of teams within a given professional league. Unlike every other industry where companies strive to out-perform their rivals and drive them out of business, sport teams rely on some level of success of their competitors in order to stay viable. A league that saw its weakest teams continually struggle to compete and go out of business would soon fail entirely due to a lack of available teams to play games. Therefore, "competitors must be of approximately equal 'size' if any are to be successful" (Rottenberg 1956, pg. 242). This unique nature of professional sports forms the basis of the uncertainty of outcome hypothesis, which asserts that fans are most interested in games where there is uncertainty as to which team will be the victor and in leagues where there is uncertainty as to which team will win the championship. A league with a focus not only in remaining viable but also in maximizing league-wide revenues would therefore seek to ensure a level of competitive balance amongst teams that maximized the uncertainty of outcome.

Neale (1964) furthers this theoretical discussion of the importance of competitive balance by extending the analysis to individual sports. In what he deems the Louis-Schmeling Paradox, Neale describes how the heavy-weight boxing champion (in this case Joe Louis) wants to face an opponent that has a legitimate chance to win (in this case Max Schmeling) in order to increase fan interest and the corresponding profits from fighting him. Although a lesser opponent would mean an easier victory, decreased fan interest in this more certain outcome would lead to lower prize money and prestige. And in the worst case scenario, Joe Louis doesn't have anyone to fight and therefore earns no income. In addition, the author discusses the importance of season-long competitive balance for a team sport league, described as the "league standing effect." This form of competitive balance finds fans interested in the daily changes in the standings or merely in the possibility of those daily changes. As the season goes on, closer standings will increase fan interest and drive larger gate receipts.

Quirk and Fort (1992) continue this foundational discussion of the need for competitive balance in the four major professional sport leagues. Following Rottenberg (1956) and Neale (1964), Quirk and Fort assert that a key determinant for fan interest in a league is the excitement generated from close games and the uncertainty surrounding which team will win. Furthermore, sport leagues must act to ensure that the level of playing talent across teams is approximately equal so that the uncertainty of outcome is preserved. If leagues are competitively unbalanced, with playing talent concentrated in just a few good teams, the authors argue that fan interest in the weaker teams will diminish, followed thereafter by a decrease in fan interest for the strong teams as well. To support these assertions, the authors give several examples where dominance by an individual team eroded league-wide attendance. For example, the Cleveland Browns of the All American Football Conference (AAFC) won all four AAFC championships during the league's existence from 1946-1949 before a partial merger with the NFL. During that reign of Browns dominance, the team saw its per game attendance drop from 57,000 in 1946 to under 30,000 in 1949. Similarly, the dominating runs of the 1927 New York Yankees and 1931 Philadelphia Athletics (who won the American League by 19 games and 13 games, respectively) contributed to overall league-wide attendance drops of 300,000 and 800,000 respectively. In the latter case, the Athletics themselves witnessed a drop in attendance of 100,000 during their dominant season. Although merely anecdotal, these examples provide support for the idea that maintaining competitive balance amongst teams (ensuring that there is uncertainty of outcome) is an important determinant of fan interest and therefore the financial livelihood of a professional sports league.

To further define what is meant by competitive balance and the corresponding uncertainty of outcome, Cairns (1987) segments the concept into three distinct branches. First, there is the uncertainty with respect to individual games (match uncertainty; game uncertainty) where competitive balance can be measured as some level of the difference in talent between the two competing teams. Second, there is the uncertainty with respect to individual championships (seasonal uncertainty; within season uncertainty; intra-seasonal uncertainty) where competitive balance can be measured as some level of the difference in the final season-long standings of all teams within a league. And third, there is uncertainty with respect to multiple championships across seasons (consecutive season uncertainty; across-season uncertainty; inter-seasonal uncertainty) where competitive balance can be measured as some level of the concentration of championships among the teams within a league. In addition to these three broad forms of competitive balance/uncertainty of outcome, Fort and Maxcy (2003) suggest that there are two main streams of competitive balance research. The first is deemed "analysis of competitive balance" (ACB) research, which empirically measures what has happened to competitive balance over time or as a result of institutional changes (such as free agency or revenue sharing) in professional sports leagues. The second is deemed "uncertainty of outcome hypothesis" (UOH) research, which measures the fan response to differences in competitive balance within a league over time.

Although not mentioned by Fort and Maxcy, a third stream of competitive balance research can be identified which involves theoretical modeling of professional sports leagues in order to determine the hypothetical effects of institutional rule changes on competitive balance. This theoretical modeling is rooted in the second main contribution from Rottenberg (1956) concerning competitive balance, which is known as the invariance principle. This principle states that under a certain set of reasonable assumptions, the initial allocation of resources has no effect on the final distribution of those resources. The primary applicability of the invariance principle to professional sports and competitive balance involves the concept of the reserve system, which existed in all of the Big Four leagues into the 1970s and which essentially bound individual players to specific teams for their entire playing career. The opposite of the reserve system is complete free agency, where players are allowed to sell their services to the highest bidder among all of the teams in the league. The team owners argued that the reserve system was necessary to preserve competitive balance, as without it, nothing would prevent large-market, rich teams from buying up all of the playing talent and creating competitive imbalance. However, Rottenberg argues that the reserve rule does not change owners' behavior, as trades and cash sales facilitate the transfer of players such that they end up on the team with which their value is highest, just as in a free labor market. A simple example can illustrate this point, where a star player initially plays for a small market team where he generates $5 million in revenue per year for the team. If he were to play for a large market team, he would generate $10 million in revenue per year for the team due to the additional revenue potential of the larger market. In this case, any trade or cash offer from the large-market team to the small-market team for the player that was valued at between $5 million and $10 million per year would be financially beneficial for both teams and the trade should occur. Thus, players should end up on the team for which their marginal revenue product is the highest, just as in free agency. As a result, instead of preserving competitive balance as the owners proclaim, Rottenberg states that the true purpose of the reserve rule is simply to depress player salaries due to the unequal bargaining power in the reserve system's monopsony market, where every player can only sell his services to one team.

Building on this theoretical foundation, El-Hodiri and Quirk (1971) introduce a mathematical model to formally prove some of the assertions concerning the importance of competitive balance for a league. Using an n-team decision making model, the authors show that as long as different markets have different revenue potential based on local team success, perfect competitive balance is inconsistent with league-wide profit maximization. This conclusion suggests that the owners' arguments in favor of certain restrictions such as the reserve clause as necessary means to promote competitive balance are largely unfounded as perfect balance is not a desired outcome for the league as it was currently constructed. However, the authors also use their model to show that perfect competitive balance can be achieved if, among other things, cash sales of players are prohibited under the reserve clause. El-Hodiri and Quirk's analysis, the first formal mathematical modeling of a professional sports league, laid the groundwork for future theoretical studies that have investigated the effect on competitive balance of institutional rule changes such as the implementation of free agency, revenue sharing, luxury taxes, and salary caps. Section 2.1 reviews the literature in this area. Section 2.2 reviews the ACB literature for each of the three forms of competitive balance, highlighting how the ACB line of research is often an empirical extension of the previous theoretical analysis. Section 2.3 reviews the UOH literature for each of the three forms of competitive balance, and concludes by showing that while ACB and UOH remain largely separate lines of inquiry, they are natural complements with the results from UOH analysis informing appropriate ACB study.

2.1 Theoretical Modeling of Professional Sports Leagues

Building off of El-Hodiri and Quirk (1971), Fort and Quirk (1995) create a theoretical framework of a professional sports league that assumes that team owners are profit-maximizers and that they choose a level of playing talent to maximize their profits in an n-team non-cooperative game where revenues are only a function of win percentage and the drawing potential of a team's location. Since fans prefer to see their team win, it is natural to assume that a team's revenues are an increasing function of team win percentage. As far as team location, all of the Big Four professional leagues in the United States have exclusive monopoly territorial rights that create differences in their revenue potential based on the markets in which they reside (e.g. the New York market has far greater revenue generating potential than the Pittsburgh market due to its greater population and per capita income). In order to lessen the effect of these market differences and promote competitive balance, leagues have instituted various rules such as revenue sharing that serve to subsidize the weaker-drawing teams. However, the authors show that with the exception of salary caps, none of the devices meant to promote competitive balance actually achieve such a result.

With no market restrictions in the theoretical model, the equilibrium profit-maximizing situation is for large market teams to purchase more playing talent and have higher win percentages than the small market teams. Two significant market restrictions meant to reduce this large market advantage are the reserve clause and the reverse order draft, both of which are shown in this model to have no effect on competitive balance in keeping with the invariance principle put forth by Rottenberg (1956). In both cases, it is expected that small market teams will simply sell their best players to the large market teams where their revenue generating potential is the highest, thus restoring the competitive dis-equilibrium found in the case with no market restrictions (free agency).

Instead of having the effect of promoting competitive balance, as often claimed by owners as justification for needing these market restrictions, Fort and Quirk show that the reserve clause and the rookie draft largely have the effect of depressing player salaries. The same is true of revenue sharing agreements, both gate/local TV revenue sharing as well as national TV revenue sharing. In either case, the transfer of revenue from the strong-drawing teams to the weak-drawing teams increases their financial livelihood, but it does nothing to change the underlying differences in revenue generating potential between the teams, and the corresponding equilibrium points of win percentage that maximize profits. However, because each win is now worth less to an individual teams due to revenue sharing, the value of additional talent is reduced and player salaries are lowered correspondingly.

The one institutional control that Fort and Quirk (1995) suggest can lead to greater competitive balance is the salary cap, where all teams are forced to spend within an upper (cap) and lower bound (floor) on total player payroll. Although such a result is shown to reduce overall league profitability and create the incentive to cheat (e.g. large market teams will want to spend more than the cap on playing talent and earn more wins, while small market teams will want to spend less than the floor), a properly enforced salary cap should have beneficial effects on competitive balance. This result is replicated by Kesenne (2000a), where it is shown that even in the case of just a salary cap (with no salary floor and no revenue sharing), the cap promotes competitive balance.

Vrooman (1995) builds on the analysis from Fort and Quirk (1995) by utilizing less limiting assumptions that allow the revenue and cost elasticities of winning to vary across teams. Under this specification, the relationship between the competitive equilibrium and market size is more complicated and requires knowledge about the specifics of the revenue and cost functions for different teams. Nevertheless, this more expansive model replicates the finding that revenue sharing should have no effect on competitive balance.

Kesenne (2000b) adds to the theoretical modeling by considering team revenues as a function of not only market size and winning percentage but also away team winning percentage, under the premise that fans prefer to see games with quality competition. Under this specification, Kesenne shows that revenue sharing can impact competitive balance as long as the downward shift in the demand curve for playing talent is not the same for all teams. If visiting team winning percentage is excluded from the model, or if the impact of home and away team quality on revenue is assumed to be the same for all teams, then revenue sharing will not affect competitive balance as was found in previous studies. Although these results were for the standard economic assumption of profit-maximizing owners, the same model was further expanded to include win maximizing owners with the finding that revenue sharing in this case impacts competitive balance regardless of whether the visiting team winning percentages is an important determinant of team revenues.

Vrooman (2009) furthers the analysis of the effect of revenue sharing and salary caps on competitive balance by considering closed and open leagues, as well as win-maximizing and profit-maximizing owners. As was shown in previous studies using profit-maximizing owners, the asymmetry of market size leads to competitive imbalance. This imbalance is worse for closed leagues (leagues with monopoly territorial rights such as in the Big Four leagues) as compared to open leagues (leagues with freedom of entry to create new teams in any market such as in European football). Adding revenue sharing to the closed league does not change the level of competitive balance, but revenue sharing in an open league is shown to reduce competitive balance. The effect of a salary cap is to increase competitive balance, but this effect is negated by the addition of revenue sharing which causes the league to revert to its original level of imbalance. In order for a payroll cap plus revenue sharing to increase competitive balance, a payroll minimum is necessary. For win-maximizing leagues, the model shows that although the original level of competitive balance is worse than for profit-maximizing leagues, the implementation of revenue sharing, payroll caps, or both can increase the level of competitive balance. This result is in contrast to Fort and Quirk (2004), who show that in consideration of win-maximizing and profit-maximizing leagues, it is indeterminate as to which league would show greater competitive balance. Instead, these two types of leagues can be identified by the fact that win-maximizing leagues have higher talent costs and greater demand for talent.

Szymanski and Kesenne (2004) add to the theoretical model by eliminating the assumption that the total supply of talent is fixed and therefore their model does not require that the acquisition of a given unit of talent by one team necessarily reduces the level of talent of the other team by the same level. Without this limiting assumption it is shown that increasing the level of revenue sharing actually causes a reduction in the level of competitive balance. This result is replicated by Kesenne (2005) for profit-maximizing owners, but in a league of win-maximizing owners, revenue sharing is expected to increase the level of competitive balance. For the standard profit-maximizing case, the implementation of revenue sharing decreases the demand for talent for all teams (thus lowering player salaries), but the reduction is lower for the teams with higher levels of playing talent and thus competitive balance is diminished.

Miller (2007) shows that the pool revenue sharing system currently employed by the MLB and NFL (where each team pays the same percentage of its local revenues into a central fund) proportionally lowers the free agent reservation price of all teams such that the level of competitive balance is unchanged. However, changing the revenue sharing system such that higher revenue teams pay a larger percentage of their revenues into the sharing fund than lower revenue teams can affect competitive balance by lowering the reservation prices of the higher revenue teams by a greater amount than that for the lower revenue teams. Furthermore, if the percentage of shared revenue received by each small market team is an increasing function of win percent, than the reservation prices of small market teams can actually be raised, and competitive balance can be increased as a result.

Chang and Sanders (2009) replicate this result concerning pool revenue sharing and competitive balance, but additionally show that this type of revenue sharing could actually worsen balance. The reason for this is that low revenue teams face a moral hazard problem where spending the revenue sharing money on upgrading their playing talent is less profitable than just keeping the money. As a result, overall spending on player talent decreases in a pool revenue sharing system while at the same time the difference in win percentage between the high revenue and low revenue teams is increased. Chang and Sanders propose and theoretically show that a pool revenue sharing system combined with minimum payroll levels that all teams must reach has the potential of increasing competitive balance by forcing low revenue teams to invest their revenue sharing funds in team improvement.

Crooker and Fenn (2007) show that, given a casual relationship from competitive balance to fan interest, leagues will under-provide competitive balance based on individual team owners acting to maximize their own (and not league-wide) profits. This result is conceptually similar to the free market economic outcome of public goods being under-provided, where in this case the public good is competitive balance. Crooker and Fenn show that competitive balance can be restored, and league-wide profits maximized, if a tax and lump-sum payments are enforced. Dietl et. al. (2010) further this discussion of the effect of luxury taxes on competitive balance, showing that a luxury tax that taxes payroll above the league average and redistributes the revenue proportionally to below average payroll teams will increase the level of competitive balance in the league. This is because small market teams end up spending more on player salaries in the luxury cap system while large market teams either spend less, or increase their spending to a degree that is smaller than that seen for the small market teams. The observed increase in competitive balance also rises as the luxury tax rate rises.

Grossman et. al. (2010) further the analysis of the effect of revenue sharing on competitive balance by using a dynamic contest model with an infinite time horizon. Unlike all of the previous studies using just a single period, Grossman et. al. emphasize that team investments in playing talent are often multi-year commitments that are expected to yield returns over time. As a result, analysis of just a single period is insufficient to properly model team investment behavior. Using this dynamic model, it is shown that the impact of revenue sharing on competitive balance depends on three factors: the cost function of talents investments, the clubs' market sizes, and the initial endowments of talent stock. Based on differing combinations of these three parameters, the invariance principle holds only in the case where all teams have the same market size. Under this situation, the long term equilibrium of the league will always be complete balance regardless of the degree of revenue sharing. For teams with different market sizes, revenue sharing is shown to decrease the long-run level of competitive balance by creating a disincentive for the small market teams to invest in playing talent. In this case, there is a greater marginal impact to a decreased investment in a small market team's talent (due to the revenue share from the large market teams, which are now more successful) than to an increase in its own talent. Revenue sharing is also shown to decrease the rate of convergence to a more balanced long-term state when there is an initial unequal endowment of playing talent. Grossman et. al. conclude that league managers intent on increasing competitive balance should lower the degree of revenue sharing.

Dietl, Grossman, and Lang (2011) add to the theoretical model by considering sport leagues composed of utility maximizing owners. Previous research has assumed that leagues are either composed of profit-maximizing owners or win-maximizing owners. In contrast, this study assumes that owners maximize utility, some weighted combination of wins and profits. In this situation, the equilibrium win percentages between a large and small market team may be closer to competitive balance if the small market team has a greater preference for wins than the large market team. In fact, if its preference for wins is large enough relative to profits, the small market team could be the dominant team in equilibrium. In regards to revenue sharing, it is shown that revenue sharing can lead to greater competitive balance if it has a positive effect on marginal revenue, an outcome that is impossible in a purely profit-maximizing league. However, if revenue sharing has a negative effect on marginal effect, competitive balance will worsen.

Dietl, Lang, and Rathke (2011) more thoroughly analyze the joint effect of pool revenue sharing and salary caps/floors. It is shown that if neither the cap nor floor is binding, revenue sharing has no effect on competitive balance, but merely lowers player salaries. If the cap is binding for the large market team but the floor is not binding for the small market team, revenue sharing decreases competitive balance and the imposition of a stricter salary cap would increase balance. If the cap is not binding for the large market team, but the floor is binding for the small market team, revenue sharing increases competitive balance as does the imposition of a stricter salary floor. Lastly, if the cap (or floor) is binding for both teams, then the league is perfectly balanced and revenue sharing will not have any effect on this balance.

In total, this stream of literature that theoretically models the economics of a professional sports league showcases the complexities involved in competitive balance research. Although there is some general agreement across studies concerning the validity of the invariance principle as it relates to the reserve clause and the reverse order draft, the impact of revenue sharing on competitive balance depends heavily on the specifics of the underlying model, with results ranging from increasing balance, to having no effect on balance, to decreasing balance. In addition, the effects of salary caps/floors, luxury taxes, and all of the various potential forms of revenue sharing are all inter-related and impact competitive balance in complex ways. As a result, the second major stream of competitive balance research, analysis of competitive balance, seeks to empirically test the ideas put forth by these theoretical models. However, empirically measuring competitive balance raises further complications, as all of these theoretical models simply use the distribution of playing talent among teams as the metric for the level of competitive balance in a league. Directly observing the level of talent on each team as a practical exercise is impossible, so new measures are needed (such as win percentages) which proxy for talent. There are a large number of different measures for each of the three forms of competitive balance (match, seasonal, consecutive season), and no general consensus as to which is preferable for each form. These different measures, and well as the ACB findings from using them, are reviewed in the next section.

2.2 Analysis of Competitive Balance (ACB) Research

Analysis of competitive balance (ACB) research involves empirically measuring the level of competitive balance in professional sports leagues. The purpose and contribution of such research is threefold. First, the relative level of competitive balance for a given league can be determined over time, such that conclusions can be drawn concerning the observed improvement or worsening of competitive balance. Second, the relative level of competitive balance can be compared across leagues. And lastly, competitive balance can be measured before and after institutional changes such as free agency in order to provide an empirical test for the invariance principle and other conclusions put forth by the theoretical modeling in the previous section. The vast majority of ACB studies to date have looked at seasonal measures of competitive balance and as a result the review of the ACB literature will start there. Later sections will review consecutive season studies and then match level studies.

2.2.1 Seasonal Competitive Balance Measures

The first seasonal competitive balance measure used by early scholars is the standard deviation of final season win percentages (or league points). The idea is that the more spread-out are the final standings, the less competitive balance exists between the teams in that season. In this regard, high values for the standard deviation of win percentages are associated with low levels of competitive balance, and perfect balance occurs when the standard deviation is zero. Cairns (1987) uses this measure to assess the impact of the re-organization of the Scottish Football League in 1975 on seasonal competitive balance. Using data from 1971-1980, the author shows that the re-organization of the top division from 18 teams to 10 teams in 1975 did not affect the seasonal uncertainty of outcome.

Scully (1989) uses the standard deviation of win percentages to investigate the level of competitive balance in MLB throughout its history (1876 through 1987). Over this time frame, the level of seasonal balance shows a small but constant increase over the entire history of MLB, suggesting that playing strengths have become more equal over time. Scully also uses this measure to assess the effect of free agency on competitive balance by comparing the period of 1961-1976 with the period of 1977-1987, finding no change in competitive balance for the American League (AL) and an increase in competitive balance in the National League (NL) after free agency was implemented in 1976. Balfour and Porter (1991) show similar results using the same seasonal balance measure and MLB data from 1961-1989. Comparing the pre- and post-free agency periods, a statistically significant decrease in the standard deviation of win percentages from 56.6 to 48.3 (increased balance) was found. Fort and Quirk (1995) use standard deviation data from 1966-1975 as the reserve period and from 1976-1985 as the free agent period, finding that competitive balance stayed the same in the NL but went down slightly in the AL, although the result was not significant. The results from these studies show that over the periods measured, the final standings are equally or more tightly bunched under free agency than under the reserve clause, suggesting that free agency might actually promote competitive balance. This is in stark contrast to the owners' arguments that the reserve clause was necessary to maintain the financial viability of the league otherwise large market teams would dominate.

Quirk and Fort (1992) introduce three additional measures of seasonal uncertainty of outcome that are based on the standard deviation of win percentages. First, they calculate the range of win percentages of each league by subtracting the lowest win percentage from the highest, giving a measure of the overall spread of team talent in a league. However, this method does not account for what is happening with the remainder of teams that are not the very best or worst, and therefore this method is not as informative as the standard deviation of win percentages. However, the standard deviation of win percentages suffers from the fact that it cannot be used to accurately compare competitive balance across leagues, since even in a perfectly balanced league the standard deviation will be larger in a league with fewer games due to chance (just like flipping a coin will likely deviate significantly from 50% heads and 50% tails for a low number of flips). As a result, Quirk and Fort calculate the ratio of the actual (observed) standard deviation of win percentage to the idealized standard deviation of win percentage, where the idealized standard deviation is determined from a normal distribution of the outcomes for a league where every team has a 50% chance of winning each of its games. Sticking with this general framework, the last new seasonal measure is the calculation of excess tail frequencies by subtracting the ideal percentage of teams that should fall outside some level of win percentages (say, +/- 2 or 3 idealized standard deviations) under perfect competitive balance from the actual percentage of teams that do so in a given year. Using all of these measures, Quirk and Fort calculate the level of competitive balance in each of the four major professional sport leagues throughout their history, finding that in general, the NFL has shown the greatest level of competitive balance and the NBA the least, with the NHL and MLB in the middle. Additionally, by looking at these measures of competitive balance for MLB and the NBA before and after free agency was implemented in each league, it is found that there were no statistically significant changes in the level of competitive balance pre/post free agency, a result in line with the invariance principle.

Other studies that have investigated the effect of free agency in MLB on seasonal competitive balance include Depken (1999), Schmidt and Berri (2001) and Schmidt and Berri (2003). Depken used data from 1920-1996 and the Hefindahl-Hirschman Index (HHI) as a measure of the concentration of wins among all teams in a season, finding that free agency had no effect on competitive balance in the NL, but a significant negative effect in the AL. Schmidt and Berri (2001) used data from 1901-1999 and the Gini coefficient, a measure of inequality that ranges from 0 (perfect equality; each team has a 0.500 win percentage) to 1 (perfect inequality), finding that competitive balance has increased for both leagues following free agency. Schimdt and Berri (2003) used data from 1901-2000 and the ratio of actual to idealized standard deviation of win percentage, finding that free agency did not have a statistically significant effect on balance. These three studies show an inconclusive effect of free agency on competitive balance (see Maxcy and Mondello 2006 for a more thorough review of such findings), a result that may be attributed to the different methodology used in each study and/or the different seasonal measures of competitive balance. However, all three measures confirm the results from previous studies that the level of seasonal competitive balance in MLB has increased over its history.

Schimdt and Berri (2003) propose that this increase in balance over time can be attributed to the increase in the underlying population of baseball talent. As MLB draws from larger and larger pools of potential players, it can be expected that there will be a greater number of especially talented players from which teams can choose, and the overall level of competitiveness will increase. To test for this, a time-series co-integration analysis is performed to determine whether the level of competitive balance responds endogenously over time with two variables that approximate the underlying population of talent: the percent of black players in the league and the percent of foreign players in the league. The results show that competitive balance is co-integrated with the measures of the population pool, suggesting that the increasing openness of the baseball players' market to blacks and foreigners over the years has been primarily responsible for the observed increase in competitive balance in MLB.

Other explanations for this increase in MLB's seasonal competitive balance over time were put forth and tested by Holowitz (1997) and Butler (1995). Horowitz used a relative-entropy measure of information theory to show that the start of the live-ball era, the racial integration of baseball, franchise expansion, and the implementation of free agency all had statistically significant effects on the broad trend of increasing competitive balance for one or both leagues in MLB. Butler used the standard deviation of win percentage to test whether free agency, the narrowing of MLB market sizes, and/or the compression of baseball talent could explain the increase in balance. The results provide no statistically significant support for any of those three theories. However, a control variable for the reverse-order amateur draft was shown to contribute positively to competitive balance. This result runs contrary to the invariance principle proposed by Rottenberg (1956).

Other ACB studies investigating the effect of the reverse-order draft on seasonal competitive balance include Fort and Quirk (1995), Croix and Kawaura (1999), and Schmidt and Berri (2003). The foundation of the reverse order draft (where the last place team in a given year gets the first choice amongst the available amateur talent the next year) is to promote competitive balance in a sports league by giving additional opportunities for better future players to the currently worse performing teams. However, the theoretical modeling described previously suggests that the reverse order draft, like the reserve clause, does not change the final allocation of playing talent and thus has no effect on competitive balance. Fort and Quirk define the pre- and post-draft periods in the NFL from 1930-1935 and 1936-1941, respectively, and in MLB from 1952-1963 and 1964-1975, respectively. Using the standard deviation of win percentages, competitive balance decreased slightly in the NFL following implementation of the draft, although the result is not significant. However, for MLB, competitive balance increases significantly following implementation of the draft for both leagues. Croix and Kawaura, in their study of the Japanese Professional Baseball League (JPBL), break down the data into three periods: pre-draft (1958-65), adjustment (1966-73), and post-draft (1974-93).

Using three different measures of seasonal competitive balance (excess tail frequencies of win percentage, range of win percentage, and standard deviation of win percentage) it is found that the draft has no statistically significant effect on competitive balance. Schmidt and Berri also find no significant effect of the draft on competitive balance in their study of MLB using the ratio of actual to idealized standard deviation of win percentages. These results for the draft are slightly more consistent than those for free agency, but there are still important differences that may be partly explained by the differences in the seasonal competitive balance measures.

Although a lot of the competitive balance research (especially the early studies) focuses on MLB, there are several studies that investigate other team sports such as the NHL (Richardson 2000; Fenn et. al. 2005; Maxcy and Mondello 2006), the NFL (Larsen et. al. 2006; Maxcy and Mondello 2006), the NBA (Fort and Quirk 1995; Maxcy and Mondello 2006), English football (Szymanksi 2001; Haugen 2008; Lee and Fort 2012); European football (Pawlowski et. al. 2010; Peters 2011), the Australian Football League (Booth 2004; Lenten 2009a), and the National Rugby League (Lenten 2009a). For the NHL, Richardson (2000) examines the level of competitive balance in the NHL over the time period of 1979-1999 using two different seasonal measures: the ratio of the actual to idealized standard deviation of win percentages and the number of playoff games played. Since the NHL has a 16-team, best of seven playoff system the number of playoff games played ranges from a minimum of 60 games (all series are four game sweeps) to a maximum of 105 games (all series last the full seven games). More playoff games would suggest greater competitive balance, with the average number of playoff games expected for a perfectly balanced league at 87.2 with a standard deviation of 3.9. The results from this competitive balance analysis show no statistically significant change in balance over time, and in fact the observed number of playoff games fall well within the 2-standard deviation expectations of perfect balance for every year in the data set. This study therefore cannot rule out the hypothesis that there is an equality of playing strength among the teams that make the playoffs. This result is in contrast to that using the ratio of actual to idealized standard deviation of win percentages, which showed a slight positive trend in seasonal balance over time.

Fenn et. al. (2005) plot the ratio of actual to idealized standard deviation of win percentages for the NHL from 1950-2000, showing that the NHL has exhibited a relatively constant level of competitive imbalance over its history but with a spike in imbalance during the 1970s. To determine the underlying factors that might contribute to the level of competitive balance in the NHL, a regression model is created that shows that the fight for talent with the rival World Hockey Association (WHA) and the 1968 expansion which doubled the number of teams from 6 to 12 both had a negative effect on competitive balance due to the dilution of talent. However, the arrival of a large number of European players had a positive effect on the level of observed balance, which Fenn et. al. find curious but which is consistent with the effect of the expansion of the labor pool for players put forth by Schmidt and Berri (2003). The results also support the invariance principle in that neither free agency nor the amateur draft had a significant effect on competitive balance.

For the NFL, Larsen et. al. (2006) examine the level of seasonal competitive balance in the NFL from 1970-2002 using the Gini coefficient and HHI of wins, showing that competitive balance in the NFL has largely hovered around a constant level. To more fully understand the components that affect competitive balance, a regression model is created that finds that the implementation of free agency and the salary cap in 1993 had a positive effect on the level of competitive balance in the NFL.

Maxcy and Mondello (2006) investigate the effect of free agency on seasonal competitive balance in the NBA, NHL, and NFL using the ratio of actual to idealized standard deviation of win percentages. For each league, each competitive balance metric is regressed on various dummy variables reflecting the different states of the league during the data set from 1951-2004. For example, in the NBA, the dummy variables are for the periods of unrestricted free agency (1978-1982), team salary cap (1983-99), team salary cap plus individual salary cap (2000-04), rival league (1967-76), strike (1999) and expansion (various years). The results are mixed, only providing statistically significant evidence that seasonal competitive balance has improved in the NHL since 1994. Maxcy and Mondello contend that the ambiguous results highlight the interactions between the granting of free agency rights and other labor market and league rules.

Fort and Quirk (1995) evaluate the effect of the salary cap in the NBA on seasonal competitive balance using the standard deviation of win percentage. Using pre-cap data from 1975-1984 and post-cap data from 1984-1993 it is shown that competitive balance actually worsened in the post-cap era. Fort and Quirk suggest that the empirical findings are inconsistent with theory due to the failure of the salary cap to actually equalize spending on player talent. As instituted in 1984 (and still continuing today), the salary cap in the NBA has many loopholes and exemptions that allow teams to regularly spend far more on payroll than the salary cap technically allows. Thus the NBA salary cap is not a great test of the underlying theory of the effect of strict salary caps on competitive balance.

Szymanksi (2001) analyzes the level of historical competitive balance in English football using the standard deviation of win percentages. Using data from 1976 to 1998, Szymanski shows that competitive balance has largely stayed the same in the English football leagues over time, despite the increasing level of income inequality. Lee and Fort (2012) use time series analysis on the level of competitive balance in the English Premier League over its entire history (1888-2007) to identify structural break points in the data. The five competitive balance measures used in this study are the ratio of actual to idealized standard deviation of win percentage, the concentration ratio of season points of the top three and top four teams, and the concentration ratio of season points of the bottom three and bottom four teams. An increase in the first three measures suggests less competitive balance while an increase in the last two measures suggests greater competitive balance. Time series analysis of these five metrics gives several structural break points that segment the data into four general periods: Early Period (1888 to the early 1900s), Pre-War Period (mid 1900s to late 1930s), Post-War Period (mid 1940s to mid 1990s), and Modern Period (after the mid 1990s). The results show that the level of seasonal competitive balance was largely increasing in the Early and Pre-War Periods, with a decreasing trend in the years after and a particularly sharp decrease in the Modern Period such that competitive balance is at a historic low in the current decade. The authors hypothesize that changes in the Champions League format, growing revenue inequality, and/or the Bosman ruling in 1995 may have contributed to the observed rapid decline in competitive balance in the 1990s and onward.

Haugen (2008) assesses the impact of the change from the 2-1-0 to the 3-1-0 points system in European football, which was implemented under the idea of encouraging more offensive play. However, a potentially unintended side effect of this change is that by inducing more offensive play, and thus more wins as opposed to draws, the level of competitive balance is predicted to decline. To test this empirically, three leagues of different quality are chosen (English Premier League, Norwegian Tippeligaen, and Romanian Divizia A) and the level of seasonal competitive balance is calculated for the period prior to and following the rule change. In each case, there is a statistically significant decrease in the level of competitive balance in the years following the rule change. Haugen suggests that the intended effect of increased interest and attendance due to greater offensive play from the rule change may be offset by a reduction in interest and attendance due to diminished competitive balance following the UOH.

Pawlowski et. al. (2010) use various seasonal competitive balance measures to determine the effect of the 1999-2000 increase in Champions League payouts on the level of balance in five top European football leagues (England, Spain, Italy, Germany, and France). The hypothesis is that the large increase in Champions League payouts for participating teams that was put in place in the 1999-2000 season created a positive feedback loop where the best teams would continue to get better, and competitive balance would worsen as a result. Depending on the league, the top three or four teams directly qualify for the Champions League and receive the large payout for participating. These teams then have substantially more money to spend on players and are likely to become better and qualify for the Champions League in the following years as well. To test this hypothesis, three different seasonal competitive balance measures were calculated for the pre (1992-2000) and post (2000-2008) payout change periods: HHI of league points, concentration ratio of points of the top five teams in each league, and standard deviation of league points per season. The results for each of these metrics generally suggest that the level of competitive balance has declined for each league following the changes in the Champions League payouts. However, none of the results are tested for statistical significance, so the observed reduction in competitive balance across the various metrics may not be meaningful.

Peeters (2011) empirically estimates the effect of various factors on seasonal competitive balance in European football using data from 32 leagues from 2000-2009. Two different competitive balance measures are used: the ratio of actual to idealized standard deviation of win percentage, and the ratio of actual to most unbalanced standard deviation of win percentage. The results for each measure identify two variables that are consistently statistically significant. First, the variation of team market sizes within a league has a negative effect on competitive balance: as the drawing potential of clubs becomes more equal, competitive balance improves. Second, the number of qualifying Champions League teams/the amount of Champions League prize money earned by a league has a negative effect on competitive balance: as the number of qualifying teams/prize money is reduced, competitive balance improves.

Booth (2004) analyzes the level of seasonal competitive balance in the Australian Football League (AFL) during its entire history (1897-2004) using the ratio of actual to idealized standard deviation of win percentage. The results show that the competitive balance in the AFL has fluctuated quite largely from year to year, but has mostly hovered around the historical average. Breaking the data up into six periods representing different structural eras in the AFL shows that the most recent period of 1985-2004 (which saw the league adopt a salary cap and player draft, in addition to previously implemented forms of local and national revenue sharing) has the greatest level of competitive balance.

Lenten (2009a) investigates the level of seasonal competitive balance in Australia's two major professional sport leagues: the AFL and the National Rugby League (NRL). Using the actual to idealized ratio of the standard deviation of win percentages it is shown that the NRL has consistently had a greater level of seasonal competitive balance across its history compared with the AFL.

Berri et. al. (2005) use the ratio of actual to idealized standard deviation of win percentages to determine the average level of competitive balance for 17 sport leagues across five sports (soccer, football, hockey, baseball, basketball). The results show that the level of competitive balance is very similar across leagues for each sport. For example, the seven soccer leagues studied have ratios from 1.281-1.581 while the two basketball leagues have ratios of 2.542 and 2.601 (higher ratios mean less balance). The authors conclude that the level of competitive balance is primarily a function of the sport being played, and that the fundamental driver of balance (or the lack thereof) is the size of the available population of playing talent. It is noted that the level of competitive balance for each of the major U.S. professional sport leagues except for the NBA has increased in the 1990s compared to their historical averages and this is attributed to the expansion of the labor pool due to the use of racial minorities and foreigners. As the pool of potential playing talent is widened, the variability of skill among those making the major leagues is expected to decrease, leading to greater balance. It is hypothesized that the reason why the NBA has the worst level of competitive balance and why it has not improved over time is that there is a very limited supply of extremely tall people in the world. This restricted supply of tall players ensures a high level of variability in their talent level and a correspondingly low level of competitive balance. Berri et. al. (2005) conclude that competitive balance (or lack thereof) is largely a function of the sport being played and therefore is unaffected by structural changes within leagues.

In addition to professional leagues, a small sub-stream of ACB literature has focused on major college football in order to investigate the effect of NCAA rule changes on competitive balance. Bennett and Fizel (1995) look at the landmark 1984 Supreme Court decision that gave each individual school property rights for their television broadcasts of their games. Prior to 1984, the NCAA controlled all of the broadcast rights and sold national packages to television networks under the argument that such a system was necessary to maintain competitive balance by ensuring smaller market teams would have relatively equal access to national exposure. However, others argued that weaker teams would have a greater ability to use television to attract good recruits if they controlled their own TV rights. Using the ratio of actual to idealized standard deviation of intra-conference win percentage for the top nine conferences in college football, the periods of 1980-83 (NCAA controlled rights), 1985-1988 (short term school controlled rights), and 1988-1991 (long term school controlled rights) are compared. For the short run period, two conferences showed a statistically significant increase in competitive balance but two others showed a statistically significant decrease. For the long run period, no conferences showed a statistically significant difference with the 1980-83 pre-period. These results suggest that the ownership of the TV rights has no lasting effect on competitive balance.

Sutter and Winkler (2003) look at the implementation of scholarship limits for Division 1 football by the NCAA in 1977. On the surface, scholarship limits have the appearance of reducing the ability of the top teams to sign an excessive amount of talent and therefore this should increase competitive balance. However, there are reasons to suggest that the true motivation of the NCAA is to preserve the success and monopoly rents of the top football programs. To test this, the ratio of actual to idealized standard deviation of win percentages is used to look at the pre- (1957-1976) and post-scholarship limit (1982-2001, allowing a five year transition) periods. The results show that competitive balance decreased after the scholarship limits were introduced.

Depken and Wilson (2006) look at NCAA investigations in Division 1A college football. The competitive balance measure used is the HHI of conference wins for each team in each of the 11 conferences studied during 1953-2003. The results show that both measures of the level of NCAA enforcement are statistically significant and contribute to greater levels of competitive balance. Conversely, the severity of probation contributes significantly to a lower level of competitive balance. The net effect of the average levels of both enforcement and probation is to promote greater competitive balance, thus giving support to the stated mission of the NCAA of ensuring a level playing field.

Dittmore and Crow (2010) look at the implementation of the Bowl Championship Series (BCS) in 1998. Competitive balance is measured using the ratio of actual to idealized standard deviation of win percentages and between-seasons using the HHI of league championships. Using data from 1993-2007 for the six BCS conferences (Big Ten, Big 12, ACC, SEC, Pac 10, and Big East) it is shown that seasonal competitive balance has improved for each of these six conferences following implementation of the

BCS. Nevertheless, the findings suggest that the implementation of the BCS did not decrease the level of competitive balance in major college football, and perhaps may have led to a slight improvement.

ACB research has also been undertaken for individual sports such as the Olympics (Baimbridge 1998), tennis (DuBois and Heyndels 2007; Corral 2009), and Formula One racing (Mastromarco and Runkel 2009). Baimbridge uses the ratio of medal winning countries to total participating countries and shows that this measure has a large negative trend, with a peak of 90.9% of competing nations winning a medal at the 1908 London Games and a low point of 32.7% in the 1988 Seoul Games. DuBois and Heyndels (2007) investigate the differences in seasonal competitive balance in men's (Association of Tennis Professionals, ATP) and women's (Women Tennis Association, WTA) tennis. The competitive balance metric is the coefficient of variation (standard deviation over the mean) of rankings points for the top 10 players on each tour, where a higher coefficient of variation means that the rankings points of the top 10 are more spread out and thus there is less competitive balance. Using data from 1995-2005, it is shown that there is no statistically significant difference in the coefficient of variation between the ATP and WTA and therefore the level of competitive balance is equal between both tours.

Corral (2009) investigates the level of competitive balance in Grand Slam tennis events following the change from 16 to 32 seeded players in 2001. Because seeded players cannot face each other until later rounds, it is hypothesized that increasing the number of seeded players will likely have the outcome of lessening the chances of early round upsets and thus decreasing the level of competitive balance in a given tournament.

To test this, the number of seeded players that reach each round of the tournament as a percentage of the total number expected to reach that round (based on their seeds) is calculated. This percentage ranges from 0 to 100% for each round, with increasing levels representing a greater amount of competitive imbalance. Using data from Grand Slam tournaments from 1994 to 2008, it is graphically shown that the level of competitive balance has decreased following the 2001 seeding change. Regression analysis confirms this result, with a statistically significant decrease in the level of competitive balance in the 2001-2008 period as compared with 1994-2000. Moreover, splitting the data into men and women shows that there was no statistically significant change in the women's tour while the magnitude of the decrease was larger for the men than originally estimated. However, the men's tour still showed a statistically significant greater level of competitive balance than the women's tour, even after the seeding rule change. These results stand in contrast to those of DuBois and Heyndels (2007), emphasizing the importance of the choice of competitive balance measure.

Mastromarco and Runkel (2009) look at the impact of Formula One rule changes on seasonal competitive balance using as the standard deviation of final championship points. The results show that the number of rules changes significantly increases the resulting level of competitive balance, with each 10% increase in the number of new regulations reducing the standard deviation of final championship points by between 7.3% and 7.8% (greater competitive balance). This provides support for the notion that Formula 1 is actively adjusting its rules in order to increase the level of within-season competitive balance.

2.2.2 Consecutive Season Competitive Balance Measures

Although the vast majority of ACB studies focus on seasonal measures of competitive balance, many of those studies also include measurements of consecutive season competitive balance which allows for differences between these two forms of balance to be easily observed. For example, Cairns (1987), in his study of the re-organization of the Scottish football league found that consecutive season uncertainty increased as measured by the concentration of championships for the ten year period following the re-organization as compared with the ten years prior. This result is in contrast to the seasonal uncertainty which stayed the same following the re-organization. Other studies showing different results for across-season competitive balance measures as compared to the previously discussed within-season measures as are follows. Scully (1989), using the distribution of league championships in the AL and NL, found that consecutive season balance decreased over time, in contrast to the increasing seasonal balance. DuBois and Heyndels (2007), using the root mean square of Spearman's rank correlation coefficient for the top 10 players year-to-year and the percent of new players making the top 10, found that the ATP has a statistically significant greater level of inter-seasonal competitive balance than the WTA, in contrast to equivalent levels of seasonal balance. Butler (1995), using season-to-season win correlations in MLB, found that free agency, the narrowing of market sizes, and the compression of baseball talent were all statistically significant explanatory variables for the observed increase in consecutive season competitive balance over time, in contrast to none of them significantly explaining the increase in seasonal balance.

Lenten (2009a), using the frequency of premiership victories for every team in the AFL and NRL, found that the AFL generally has a greater level of multi-season competitive balance, in contrast to the NRL having greater within-season balance. Dittmore and Crow (2010), using the HHI of league championships, found that consecutive season balance decreased for three of the six BCS conferences following the implementation of the BCS, in contrast to the increase in seasonal balance for all six conferences. Bennett and Fizel (1995), using the turnover of individual team win percentages each year, found that inter-seasonal balance increased following the 1984 Supreme Court decision, in contrast to no change in the intra-seasonal balance. Maxcy and Mondello (2006), using Spearman's rank correlation coefficient, found that inter-seasonal competitive balance has improved in the NFL since free agency was introduced in 1993 and declined in the NBA after free agency, in contrast to no change in intra-seasonal balance for both of those leagues. Sutter and Winkler (2003), using nine different measures (number of new entrants, total teams, and the HHI of AP Top-20, AP-Top 10, and conference champions), found a statistically significant increase in the consecutive season competitive balance of Division 1 football following the introduction of scholarship limits, in contrast to the decrease in seasonal balance.

The conflicting results of all of these studies when comparing seasonal and consecutive season competitive balance highlights the importance of the choice of not only the specific competitive balance measure, but also the form of competitive balance that is most appropriate for a given study. These findings also emphasize that competitive balance is not one uniform topic but rather several distinct topics under one common umbrella. As a result, simply using the term competitive balance is insufficient, as what is true for seasonal competitive balance may not be true for consecutive season balance, as shown in the previous studies.

However, not all results are different when comparing seasonal and consecutive season competitive balance measures. For example, Quirk and Fort (1992) find the same relative levels of competitive balance across the Big Four leagues when looking at the Gini coefficient of the concentration of championships as an inter-seasonal measure. Similarly, Fort and Quirk (1995) find the same results concerning free agency and the draft in MLB (more balance), and for the salary cap in NBA (less balance) using the Gini coefficient of the concentration of championships as an inter-seasonal measure. Pawlowski et. al. (2010), also find similar results concerning the increase in Champions League payouts (although more striking in magnitude) when using Markov transitional probabilities as the measure of consecutive season competitive balance. Balfour and Porter (1991) find the same results concerning the effect of free agency (increased balance) in MLB when using one-, two-, and three- year lag correlations of winning percentage for each team as measures of inter-seasonal balance. Lastly, Croix and Kawaura (1999) find similar results concerning the draft in the JPBL (no effect on balance) when using three different consecutive season measures of competitive balance: the HHI of pennant winners and last place finishers as well as the change in performance of individual teams post-draft.

In addition to the ACB research that investigated both within- and across-season measures of competitive balance, several studies have focused specifically on consecutive season measures. Eckard (1998) looks at NCAA regulation of player recruiting, eligibility, and compensation. NCAA regulation of the college football players' market began in 1952 and mirrors the situation of the reserve clause in baseball. In both cases, those in charge argued that the market restrictions were necessary to maintain competitive balance, while in reality the motivation was likely to reduce costs and maximize profitability. The difference is that MLB players were able to earn free agency in 1976, while collegiate football players are still subject to strict NCAA regulations. To test for the effect of NCAA regulation on inter-seasonal competitive balance in college, two sets of consecutive season competitive balance measures are used. The first set considers national rankings and the number of different schools to make the rankings, the concentration of schools in the rankings over time, and the frequency with which new schools or long-removed schools break into the rankings, either the top 10 or the top 20. The second set considers conference standings and the level of churn in the final standings as well as the concentration of championships. Using all of these measures, the pre-regulation period (depending on the specific test, data starts from as early as 1924 and goes through 1951) is compared to the post-regulation period (1957-1981) with five years allowed for a transitional period. The results show, across all measures, a reduction in the level of consecutive season competitive balance after NCAA regulation in 1952.

Grier and Tollison (1994) address the issue of whether the reverse order draft affects inter-seasonal competitive balance. Using NFL data from 1983-1990 to perform a regression analysis of win percentage on average lagged draft order, it is found that teams drafting earlier win more games, with a five-year draft lag showing the greatest effect.

Fizel (1997) investigates the effect of free agency in MLB on consecutive season competitive balance. The competitive balance measures are the number of teams that finished within 10 games of the league leader, the number of different division winners, and the number of different pennant winners during eight years of the reserve clause (1969-1976) and then during two eight year periods of free agency (1977-1985 with the strike shortened 1981 season excluded, and 1986-1993). The results show that the number of competitive teams, division winners, and pennant winners was the same or increased during the free agency periods as compared to the reserve clause era (e.g. for the NL the number of different pennant winners went from 4 to 6 to 7 over the three periods studied).

Eckard (2001) also investigates the effect of free agency on inter-seasonal competitive balance by using the HHI of team championships as well as the decomposition of winning percentage variance into cumulative and time variances. A standard within-season competitive balance metric used in numerous previous studies is the standard deviation of winning percentages during individual seasons. However, this metric does not account for possible churn in league standings from year to year, and therefore does not differentiate between two league years that have completely identical standings and two league years with an identical standard deviation of wins among all of the teams but with every team occupying a different final position. Eckard's variance decomposition breaks this value up into two components: the variance of cumulative win percents across league members during the period, and the mean of individual teams' annual win percent variances about their own period mean. Using this decomposition, it is possible to differentiate between the two examples given above where the total variance is the same, but in the second case the time variance will be greater and the cumulative variance will be lower, which indicates a greater level of inter-seasonal competitive balance. Using this metric for an MLB data set from 1961-1992, it is shown that while the total variance (standard deviation) of win percentage does not change significantly from the reserve clause era to the free agency period, the individual components of the variation significantly change in support of greater inter-seasonal competitive balance for both the AL and NL during free agency. The results using the HHI of championships also show increased inter-seasonal competitive balance following free agency.

Hadley et. al. (2005) study the level of inter-seasonal competitive balance in MLB before and after the 1994 strike using Markov transitional probabilities. The Markov transitional probabilities consist of four probabilities: that a playoff team from the previous season makes the playoffs in the current season, that a playoff team misses the playoffs, that a non-playoff team makes the playoffs, and that a non-playoff team misses the playoffs again. Assuming complete balance, the previous state should have no impact on the future state, and thus the probability of making the playoffs in the current season should be the same for all teams, both previous playoff and non-playoff teams. The results from the pre-strike period (1982-1993) are not statistically different from the perfect parity probabilities, but the post-strike period (1995-2003) shows a statistically significant decreased level of inter-seasonal competitive balance, as previous playoff teams are over three times more likely to make the playoffs in the current season than non-playoff teams.

Mizak et. al. (2007) investigate the level of consecutive season competitive balance in MLB over time using the adjusted churn. This metric is calculated by taking the sum of the absolute value of the change in league standing for each team and then dividing by the maximum possible churn. This yields a number between zero and one, where a value of zero represents league standings that are completely unchanged from one year to the next and a value of one represents league standings that are completely reversed (previous first place team finishes last, previous second place team finishes second to last, etc.). Computing the adjusted churn for the AL and NL from 1910 to 2007 shows a sharp decrease in the level of inter-seasonal competitive balance for the AL during the 2000s. Furthermore, it is shown that the adjusted churn was especially low for the AL East from 1997-2007, including six straight years of absolutely no change in the standings (adjusted churn equals zero) from 1998-2003.

Lee (2010) measures the level of between-season competitive balance in the NFL before and after the implementation of a salary cap and free agency in 1993. The between-season competitive balance measure is the correlation in win percentages for each team from one year to the next. Using data from 1978-2008, the results show a statistically significant increase in inter-seasonal competitive balance (a reduction in the correlation of win percentages from 0.563 to 0.444) following the implementation of free agency and a salary cap in the NFL.

2.2.3 Match Competitive Balance Measures

Although almost all of the ACB literature focuses solely on seasonal and consecutive season competitive balance measures, two of the previous articles included match-level measures. Sutter and Winkler (2003) used the average margin of victory of all division 1 collegiate football games as the measure of match uncertainty, finding that NCAA scholarship limits did not significantly affect game-level competitive balance.

DuBois and Heyndels (2007) used the percent of Grand Slam finals sets that went to a tiebreaker, and the percent of Grand Slam finals that lasted more than the minimum number of sets (more than two for women, more than three for men) as measures of game-level uncertainty of outcome. The results showed no statistically significant difference in match competitive balance between the ATP and WTA.

Two other recent articles focus exclusively on match-level competitive balance. Bowman et. al. (2012) use six different point spread based metrics (e.g. the mean absolute value of all points spreads with and without home field advantage included) to quantify the level of game competitive balance in the NBA and NFL. Calculating these competitive balance measures for the NBA from 1990-2009 and the NFL from 1985-2009 show that while they fluctuate year-to-year for both leagues, there has been a slight statistically significant increase in match competitive balance over time in the NBA and no significant change in the NFL.

Bowman et. al. (2013) extend this analysis to use pre-game money lines instead of point spreads to calculate the six match-level competitive balance metrics for MLB, as MLB uses money lines instead of the point spreads used in the NBA and NFL. Using data from 1999-2011 these competitive balance measures are calculated for MLB, and the result is a statistically significant increase in the level of match competitive balance over this time period.

2.3 Uncertainty of Outcome Hypothesis (UOH) Research

Although ACB research provides interesting information concerning what has happened to competitive balance over time and/or as a result of institutional changes in professional sports leagues, the findings may not have practical significance. In keeping with the original underlying notion that competitive balance is necessary for league health and profitability, the ACB studies assume that regardless of the competitive balance measured employed, more balance is always good and less balance is bad. But none of those studies actually test whether this is true by looking at the fan response to differing levels of competitive balance using attendance and/or television viewership. In light of this, Zimbalist (2002; 2003) questions the usefulness of previous competitive balance measures and argues for the use of one best measure to which consumers show the greatest sensitivity. In the absence of such a measure, it can be difficult to properly assess whether the presumed lack of competitive balance in MLB, the NBA, and English football is actually bad for the respective sport. Similarly, is the greater level of competitive balance in the NFL and NHL good for those sports? In addition, competitive imbalance that favors large market teams might be viewed differently by fans than competitive imbalance that favors small market teams (Kesenne 2004).

In consideration of the previous ACB findings, it is clear that the results are very sensitive not only to the form of competitive balance that is studied (match, seasonal, or consecutive season) but also to the specific competitive balance measure that is used. Testing whether fans respond to given forms and measures of competitive balance thus becomes important. If, for instance, fans show no response to varying levels of the ratio of actual to idealized standard deviation of win percentages then studies showing an increase or decrease in this metric for a given league over time are not particularly informative. In addition, testing the response of attendance and television viewership to competitive balance allows for Rottenberg's (1956) original theories concerning fan preference for competitive balance (the uncertainty of outcome hypothesis, UOH) to be empirically tested. Do fans actually prefer outcomes (at the game, season, and multiple season levels) to be uncertain/competitively balanced? Because the UOH literature focuses primarily on the match-level, the literature review starts there, followed by seasonal, consecutive season, and then combination studies.

2.3.1 Tests Using Match Competitive Balance

Peel and Thomas (1988) provide an empirical test for the individual game uncertainty of outcome hypothesis by using pre-game betting odds to analyze the effect of the probability of the home team winning on attendance for the English Football League. The attendance regression results show highly statistically significant results for both team position in the standings as well as the home team win probability for all four divisions of the English Football League. These results suggest that better quality teams will drive attendance as well as an increased probability of home team success, with a 10% increase in the chance of the home team winning (evaluated at the sample mean) increasing the attendance by 1,650 in Division One, 768 in Division Two, 580 in Division Three, and 465 in Division Four. Although Peel and Thomas assert that these findings provide support for the UOH, in fact they suggest that fans prefer more certain outcomes in favor of the home team winning.

Peel and Thomas (1992) update the previous study by including a quadratic form for the home team probability of winning (still based on pre-game betting odds) as well as including lagged attendance to account for a team's core supporters that regularly attend games regardless of other factors such as competitive balance. This study also attempted to include measures for within-season uncertainty of outcome by using dummy variables for late-season data to segregate teams into categories such as " in contention for the playoffs," "guaranteed a place in the playoffs," "promotion candidate," "relegation candidate," etc. However, the parameter estimates for these dummy variables were not significant so they were excluded from the model. In regards to the home team's probability of winning, Peel and Thomas found a result contrary to the UOH of a U-shaped relationship where attendance is maximized by lop-sided results with limited uncertainty. Czarnitzki and Stadtmann (2002) find nearly identical results in their study of the German premier football league using data from 1996-98 and an attendance demand model including even more explanatory variables. Buraimo and Simmons (2008) also find a U-shaped relationship using data from the English Premier League from 2000-2006, where attendance is minimized when the home team has a probability of winning of 0.35. This suggests that attendance is maximized when the home team has an overwhelming probability of winning, quite in contrast to the UOH. Furthermore, this relationship estimates a higher attendance when the home team has a very low probability of winning than when both teams have an equal chance of winning. Buraimo and Simmons attribute these findings to the fans' strong desire to see their home team win in combination with the enjoyment of cheering for a "David vs. Goliath" type underdog.

Although these studies using European football data sets seem to show that the UOH is completely misguided, Knowles et. al. (1992), find completely opposite results in their study of the 1988 MLB season. With a nearly identical specification, the attendance regression shows statistically significant support for an inverse U-shaped relationship between uncertainty and attendance, with attendance maximized at the point where the home team has a 0.6 probability of winning. This result supports the UOH, in that games with a priori closer expected outcomes (with a slight home team bias) lead to greater attendance, all other things equal. However, in a more recent study using numerous different attendance demand specifications for the 2007 MLB season, Lemke et. al. (2010) find the U-shaped relationship between uncertainty and attendance, such that attendance is maximized when the home team has a maximum or minimum chance of winning. In fact, the results show that attendance is minimized when the home team has a 0.54 probability of winning and that an increase of this probability to 0.75 would be expected to increase attendance by 1,910.

Peel and Thomas (1997) continue their previous investigations of the pre-game betting odds as a measure of game uncertainty although with two new considerations. First, they employ "handicap" or "spread" betting odds instead of the fixed odds from previous studies. Second, they investigate rugby league as opposed to football. Using data from the 1994-95 season, the authors initially show that the spread betting odds are efficient, and that the spread is an accurate ex-ante predictor of match results and thus a good proxy to measure outcome uncertainty. The authors then use the spread betting odds in an attendance demand regression equation to determine the effect of outcome uncertainty of demand for rugby league games. The results show, in support of the UOH, that for each additional point on the handicap value (meaning a more lopsided expected outcome), attendance is reduced by 52 in the First Division and by 9 in the Second Division. This implies that a game with a zero handicap value (or perfectly balanced) would add 523 spectators on average to a First Division match and 149 to a Second Division match.

Forrest and Simmons (2002) use match-level data from the 1997-98 season of the English Football League to test whether the expected ax-ante closeness of games (as measured by the betting odds) impacts attendance. This study mirrors those of Peel and Thomas (1988; 1992; 1997) except that the betting odds are corrected for potential bookmaker home-away bias, short odds-long odds bias, and bias in favor strongly supported clubs. This correction yields a probability ratio variable that is the chance of a home team victory divided by the chance of an away team victory. Because home field advantage in English soccer is so large, nearly all of the observations have a probability ratio greater than 1, with a ratios approaching 1 reflecting greater competitive balance. The results from the attendance demand regression show that there is a statistically significant negative relationship between the probability ratio and attendance, meaning that as matches become less balanced attendance is expected to fall. The statistically significant positive parameter estimate on the square term shows that the decline in attendance slowly levels off as the probability ratio increases and thus the greatest increase in attendance occurs as games approach complete balance. These results provide additional support for the uncertainty of outcome hypothesis for the level of individual matches.

Forrest, Beaumont, Goddard, and Simmons (2005) find nearly identical results using data from the 1997-98 season of the three divisions of the English Football League. However, these authors importantly note that completely balanced games (each team has an equal chance of winning) cannot occur for two completely balanced teams, because that would ignore home field advantage. Because of this, it is likely that league-wide attendance is maximized not when teams are completely balanced, but rather when there is sufficient variation in team ability as to maximize the number of matches between a home team that is weaker than its opponent by an amount that is exactly offset by its home field advantage. In fact, Forrest et. al. go on to show that the regression results suggest that had the English Football League consisted of perfectly balanced teams, it would have shown a reduction in attendance of over 2 million people for the season in question. These findings provide an enlightening observation in favor of the uncertainty of outcome hypothesis at the match-level, but against the presumed notion that uncertainty (and thus attendance) is maximized when teams are completely balanced.

Forrest, Simmons, and Buraimo (2005) bring the analysis of the uncertainty of outcome hypothesis to television viewing audiences for the first time. The authors argue that television audiences are of increasing financial importance to professional teams and thus warrant academic study concerning the effect of uncertainty of outcome. In addition, the use of television audiences overcomes three drawbacks from the use of gate attendance data. First, the majority of tickets sold to individual matches are from season tickets, and season ticket holders are expected to attend games regardless of the degree of outcome uncertainty. Second, many attendance data sets suffer from a large number of sell-outs, which complicates the determination of the true demand. Third, most individual match attendees are supporters of the home team, who may be more interested in the home team winning than in outcome uncertainty. These reasons might explain why the results from previous match-level uncertainty of outcome studies are so mixed, and help provide justification for the use of television audiences instead. Using English Premier League data from 1993-2002, Forrest, Simmons, and Buraimo find that greater uncertainty (measured as the absolute value of the sum of the average home field advantage and the average points per game of the home team, minus the average points per game of the away team) is a statistically significant driver of larger television audiences. Although this provides strong support for the uncertainty of outcome hypothesis for television audiences, the authors caution that the effect size is relatively small. For example, taking all variables at their means gives an estimated television audience of 888,457 per game. Increasing outcome uncertainty by one standard deviation (to the point of nearly perfect parity) adds only 74,152 to the television audience, an increase of just 6%.

Paul and Weinbach (2007) also test the UOH in regards to television audiences using Nielsen ratings for the NFL's Monday Night Football telecasts from 1991-2002. Two different regression models are used: one for the Nielsen ratings at the start of the game, and one for the difference in Nielsen ratings at half-time compared with the start of the game. At the start of the game, the uncertainty variable is the difference between winning percent of the home and away teams and at half-time the uncertainty variables is the score differential. The results show that at the start of the game, each difference of 10-percentage points in win percent between the teams (e.g. one 0.600 team and one 0.500 team) is expected to decrease the viewing audience by 168,762. Similarly, at half-time each extra point of difference in the score is expected to decrease the viewing audience by about 75,000. In both cases, the results give strong support to the UOH at the match level for television viewing audiences.

Meehan et. al. (2007) test the UOH in MLB using individual game attendances from 2000-2002 and the difference in win percent between the home and away teams as the measure of match-level uncertainty. Three specifications of an attendance demand model are utilized in order to determine the exact nature of the effect of match-level uncertainty on attendance. The first specification uses only the absolute value of the difference in win percent between the home and away team, with the results showing a statistically significant negative effect on attendance when competitive balance is reduced. For each 10-percentage point increase in the difference between the winning percentages of the home and away team, attendance is expected to be reduced by 941 fans. The second specification separates the uncertainty variable into two components: one for when the home team has a better winning percentage and the other for when the away team has a better winning percentage. The results from this specification show that the attendance response to competitive balance is asymmetric, as the effect of competitive balance is magnified when the home team has a better record (each 10-percentage point increase is expected to reduce attendance by 1,998 fans) but statistically insignificant if the away team has the better record. The third specification interacts these two variables with the number of games left in the season and the number of games the home team is behind the division leader. The results from this specification show that the attendance response to competitive balance is also sensitive to the current point in the season as well as how competitive the home team is in regards to challenging for the division crown. In general, if the home team has the better record, increases in the level of competitive balance lead to attendance increases of a larger magnitude earlier in the season compared to later, and when the home team is further down in the standings compared to competing for the division lead. When the away team has the better record, the level of competitive balance has no effect on attendance until the later stages of the season, when increasing competitive balance actually decreases attendance, which the authors attribute to the idea that late in the season fans would rather watch a great away team than a more competitively balanced game. All in all, these results suggest that the relationship between match-level competitive balance and attendance is complicated, but that overall greater levels of match uncertainty lead to greater fan interest in terms of attendance.

Coates and Humphreys (2012) further the study of asymmetric responses to match-level competitive balance by estimating an individual game attendance demand model in the NHL using data from 2005-2010. Guided by prospect theory, the authors hypothesize that fan interest in competitive balance may vary depending on whether the home team is expected to win or expected to lose, as expected gains have been shown to be treated differently than expected losses. To test this, the data is segmented into nine ranges based on the home team probability of winning (calculated from pre-game betting odds). The results show a strong asymmetric effect in that the probability of a home team win is only a statistically significant driver of attendance in the ranges where the home team is favored, with the magnitude of the effect increasing as the probability of a home team win increases. For the ranges where the away team is favored, there is no statistically significant effect of the home team probability of a win on attendance. These results provide evidence against the UOH at the game-level in the NHL.

Benz et. al. (2009) test the UOH at the match-level using data from 1999-2005 for the first division of professional German football. This study advances previous work in this area in two important ways. First, the number of season ticket holders (who are expected to attend every game regardless of the particulars of the match) are accounted for and subtracted from the observed attendance to get the dependent variable of interest.

Second, the model allows for heterogeneity of fan demand by using a quantile regression with results for five different demand quantiles: 0.10, 0.25, 0.50, 0.75, and 0.90. For robustness, five different measures of match-level competitive balance are included in separate models. The results show that none of the uncertainty of outcome variables is statistically significant except for the high demand (0.90) quantile, where three of the five variables are significant in the hypothesized direction at the 10% level. Of particular interest is that the estimates on the home team probability of winning (and its square term) suggest that attendance is maximized for high demand games when the home team has a 53% chance of winning. However, due to the fact that only high demand games show sensitivity to the level of competitive balance, and that even those estimates are significant at only the 10% level, the authors conclude that the level of uncertainty has a minor influence on demand and that league revenue re-distribution efforts to increase the level of competitive balance are misguided.

Buraimo and Simmons (2009) test the UOH at the match level using data from 2003-2007 from Spain's Primera football division. This article adds to the literature by separately estimating an attendance demand model and a television viewership demand model. The authors hypothesize that fans at the stadium will care more about a home team victory whereas the television audience will be more interested in a competitively balanced match. To reflect these hypothesized differences, two different measures of competitive balance are used. For gate attendance, it is the probability of a home team win (and its square term), while for television viewership, it is the absolute value of the difference between the probability of a home team win and the probability of an away team win. In both cases, the probabilities are calculated from the pre-game betting odds.

The results from these two models show that uncertainty of outcome has a negative effect on gate attendance but a positive effect on television audience. As in previous studies of European football, (e.g. Buraimo and Simmons 2008), attendance is maximized when either the home team has a very large or very small probability of winning. However, the opposite is true for television viewership, where greater competitive balance yields a larger audience. Using the parameter estimates from these two models as well as the average revenue generated per fan attending a game or watching on television, it is shown that a theoretical increase in the level of league-wide competitive balance would create sufficient incremental revenue from enhanced television viewership to more than offset the loss from lower attendance, a combined result in support of the UOH.

In a novel attempt to more directly measure fan response to match-level competitive balance, Paul et. al. (2011) use fan ratings submitted on nfl.com for each game during the 2009-2010 season to test the UOH. With the final margin of victory as the match-level uncertainty of outcome variable, the authors find that the victory margin has a statistically significant negative effect on fan ratings, a result in support of the UOH. Specifically, each extra point in the final margin of victory was expected to lower the fan rating by 0.28 points on a scale from zero to 100. Although this study advances the literature on competitive balance by providing a nearly direct measure of fan preferences, there are some potential issues with selection bias.

2.3.2 Tests Using Seasonal Competitive Balance

Jennett (1984), in what is considered the first empirical test of the UOH, creates a measure of individual season uncertainty for each game that ranges from zero to one, deemed the significance value. Taking into account both a team's level of contention for the championship as well as the number of games remaining in the season, the significance value would be, for example, zero if the team is mathematically eliminated, 0.1 if the team requires ten victories to win the league, and 1.0 if the team requires a single win to claim the championship. Using this significance variable for both the home and away team in Scottish league football shows that uncertainty of outcome is a significant driver of attendance for individual teams, with a home game deciding the Premier Division championship attracting on average over 12,000 extra spectators. However, although there is significant support for the importance of the uncertainty of outcome for individual teams late in the season, the same is not true for the league as a whole. A reasonable increase in competitive balance that saw the average home team significance value increase from 0.0269 to 0.0369 would lead to only 205 extra spectators per game, or 37,000 fans across the entire 180 game season, a relatively minor change compared with the 500,000 decline in Premier Division attendance from 1979-80 to 1980-81.

Brandes and Franck (2007) test whether the within-season UOH is valid for European football using data from 1963-2006 for six different leagues: German 1 Bundesliga, English Premier League, English Championship Division, Italian Serie A, Italian Serie B, and French Ligue 1. The motivation for this study is the observation of increasing attendance for most of these leagues despite the fact that they are considered to have a low level of competitive balance. Three different measures of within-season competitive balance are separately utilized: the ratio of actual to idealized standard deviation of win percentages, the concentration of season points accrued by the top five teams in each respective league, and the HHI of points. The results show big differences across the leagues and for each competitive balance measure, although the most common conclusions is that attendance is not a statistically significant function of the level of seasonal competitive balance. For the few league-measure combinations that showed attendance as a statistically significant function of competitive balance, only one had increasing competitive balance leading to increased attendance as suggested by the UOH. Brandes and Franck conclude that the relationship between attendance and competitive balance varies by country and by competition tiers within each country, but that the evidence suggests that European football attendance is not particularly responsive to the level of within-season competitive balance. This finding could be explained by the unique nature of European football as compared to the U.S. professional sport leagues, where the promotion/relegation system and the European wide competitions (such as the Champions league and UEFA Cup) create additional excitement at all levels of competitive even if each national league has wide disparities in team talent.

Lee (2004) tests the UOH in MLB, the Japanese Professional Baseball League (JPBL), and the Korean Professional Baseball League (KPBL) using data from 1976-2000. Because the KPBL is much younger than the other leagues (founded in 1982 compared with 1901 and 1936), and has far lower attendance, it is considered a developing league as opposed to the developed leagues of MLB and the JPBL. The author hypothesizes that uncertainty of outcome is more important in developing leagues because fans of developed leagues are more entrenched in their support due to their long history. To test this, three measures of within-season competitive balance are considered: ratio of actual to idealized standard deviation of win percentages, tail likelihood (a slight modification of the excess tail frequency), and the difference in winning percentage between the first and second place teams in each league. The results from the attendance demand regression show that the first two competitive balances measures are statistically insignificant determinants of attendance for MLB and the JPBL while the third is significantly negative for the AL, the Pacific League of the JPBL, and KPBL. These results give some support to the UOH, in that decreasing the level of competitive balance in a given league (by increasing the win percentage difference between first and second) leads to a reduction in league-wide attendance. Since the parameter estimate for this variable is the largest for the KPBL, and since the KPBL was the only league to show significance for either of the other competitive balance measures, the Lee concludes that developing leagues have fans that are more sensitive to the level of competitive balance.

Soebbing (2008) tests the UOH in MLB using individual team attendance data from 1920-2006 and two measures of within-season competitive balance: the ratio of actual to idealized standard deviation of win percentages, and the number of games behind the division leader. The results from the attendance regression show that both competitive balance metrics are statistically significant and that they affect attendance in the predicted direction. An increase in the standard deviation of win percentages or an increase in the number of games behind the division leader (lower seasonal competitive balance) will both lead to an expected decrease in attendance. Lee (2009), using a more expansive measure of the number of games behind the division leader that accounts for the relative standing of every team in MLB, finds similar results for the period of 1901-2006: greater competitive balance has a statistically significant positive relationship on league-wide attendance. For example, the increase in competitive balance observed in

MLB from 1994-2006 (as compared with the period of 1969 to 1993) led to an increase in AL attendance of 143,764 per year and in NL attendance by 237,233 per year. Lenten (2009b) uses the ratio of actual to idealized standard deviation of win percentage to perform a similar analysis for the Australian Football League from 1945-2005. The results show a statistically significant positive relationship between the level of seasonal competitive balance and attendance, with the increase in competitive balance in the AFL during 1995-2005 (as compared with the previous period of 1976-1985) leading to a league-wide annual attendance increase of 230,000.

Levin and McDonald (2009) test the within-season UOH using data from five non-major professional leagues: the Arena Football League, the Central Hockey League, the Major Indoor Soccer League, the National Lacrosse League, and the Northern League (baseball). The authors chose to focus on non-major professional sport leagues in order to best be able to isolate the effect of competitive balance on attendance, as these leagues are less likely to be influenced by many of the marketing factors common to major league sports. For example, non-major professional leagues usually do not have live broadcasts of games and do not have the advantage of a high level of third-party communication such as sports shows and newspaper accounts. Furthermore, these types of leagues rely heavily on gate attendance for revenues and cannot rely on the level of fan loyalty exhibited at the major league level. For these reasons, it is expected that this data set will provide clear evidence of the effect of competitive balance attendance. To provide a common dependent variable across leagues, the average attendance per game as a percentage of average capacity is used for each league-year. Using data from the inception of each league (ranging from 1985 to 1993) until 2003, the regression results show a statistically significant positive relationship between the level of competitive balance (measured by the actual to idealized standard deviation of win percentage) and attendance. This provides support for the UOH for non-major professional sports on a seasonal basis.

2.3.3 Tests Using Consecutive Season Competitive Balance

Eckard (2001) uses an attendance demand model to investigate the effect of winning streaks on team attendance, where a winning streak is defined as at least three consecutive seasons of first or second place finishes in the league standings, or third or fourth place finishes if the team is within ten games of first place or has a win percent above 0.575. The results show that winning streaks are a statistically significant negative determinant of attendance. For every additional year of a winning streak, a team that averages an attendance of about three million fans could expect an annual decline of about 51,000. This analysis provides empirical support for the inter-seasonal UOH, especially in that it shows that fans of perpetually good teams lose interest in attending games over time.

Humphreys (2002), in his review of the various measures of competitive balance found in previous scholarly work, concludes that none of these metrics adequately measure the across-season levels of competitive balance. Therefore, a new measure is proposed, the competitive balance ratio (CBR), which is the ratio of the average variation in teams' win percentages across seasons to the average variation in win percentages in each season. Essentially, this measure reduces Eckard's (2001) variance decomposition into one number that ranges from 0 (no team-specific variation in win percentages) to 1 (all of the observed within-season variance is team-specific). If fans are interested in the ability of teams to move up and down within the standings year-to-year (churn), a larger CBR should drive greater attendance. Using MLB data from 1901 -1999, the regression gives a statistically significant positive effect of CBR on league-wide attendance. The significant parameter estimate on CBR in this model is in contrast to the insignificant results using the same model except with standard deviation of win percentage or HHI of championships as the competitive balance metric. Humphreys concludes that CBR is a better metric for capturing the consumer response to inter-seasonal competitive balance in the form of attendance.

2.3.4 Tests Using Multiple Forms of Competitive Balance

In his review of the UOH literature, Fort (2006) suggests that future studies should consider all three forms of competitive balance (match, seasonal, consecutive season) in the estimation of their attendance demand models. Since then, a few studies have heeded this advice, while several others (including before Fort's article) have used two of the three. Borland (1987) was the first to use two of the three forms of competitive balance in his attendance demand model for the Australian Football League from 1950-86. Five different measures of uncertainty of outcome were used, with each measured at four different points throughout the season and then averaged. The first four are seasonal measures (e.g. the difference in games won between the first and last place teams) while the fifth is an inter-seasonal measure of the number of different teams in the finals in the past three seasons divided by the number of finals berths available. The results of the attendance regression show that only two of the competitive balance measures (both seasonal) were statistically significant predictors of attendance in the direction theorized by the UOH. Of those, the average number of games behind the league leader had the most explanatory power.

Carmichael et. al. (1999) estimate an attendance demand model for the 1994-95 English Rugby League using one match uncertainty variable and two measuring season uncertainty (one for each division). The match uncertainty variable uses handicap betting odds where the larger absolute value of the handicap, the less uncertainty of outcome and the lower expected attendance. The season uncertainty variables are pre-season betting odds for the winners for each of the two divisions where the longer the odds of a team winning its division, the less chance the team is predicted to have success during that season (lower uncertainty) and the lower attendance is expected for its games. The results of the regression confirm the hypotheses concerning the uncertainty variables, in that all three variables are statistically significant and with the correct signs.

Owen and Weatherston (2004) create an attendance demand model for the New Zealand based matches of the Super 12 rugby union competition using data from 1999 to 2001. There are five variables included to represent the level of seasonal uncertainty (e.g. the number of points that the home team is behind the last playoff spot) and two variables included to represent the level of match uncertainty (e.g. the probability of a home team win as calculated from the pre-game betting odds). Various different specifications of the attendance regression are completed but the only uncertainty variable that is ever statistically significant in any of the models is the number of games left in the season, which does not reflect fan interest in different underlying levels of competitive balance, but rather greater fan interest as the season progresses regardless of the observed competitive balance. As a result, Owen and Weatherston conclude that there is no support for the UOH in this case.

King et. al. (2012) find completely opposite results using game-level attendance data from 2004-2008 in Australia's National Rugby League (NRL). Game level uncertainty (measured by the probability of a home team win) and seasonal uncertainty (measured by the probability of the home team making the playoffs as determined through simulation) were both statistically significant drivers of attendance. These results are robust to different specifications of seasonal uncertainty including the number of points behind the current leader for the home team or the away team, the average number of points behind the current leader for the home and away teams, and the number of points required for the home team to make the playoffs. The results for game-level uncertainty suggest an inverse U-shaped relationship between attendance and the probability of the home team winning, with attendance maximized when the home team has a 0.605 chance of winning. These results provide support for the UOH in the NRL at the game-level and particularly at the season level.

Pawlowski and Anders (2012) estimate an individual game attendance demand model for the 2005-2006 season of the German first football division using match-level and seasonal uncertainty of outcome variables to explain attendance. The match-level uncertainty variable is a measure of a team's chances of winning the game while the seasonal uncertainty variable is a measure of a team's chances at winning the championship, both of which are larger as uncertainty increases. The results show that the seasonal balance variable is statistically significant and positive, as expected by the UOH, but the match measure is statistically significant and negative. This suggests that fans prefer more certain outcomes where the home team is either a large favorite or a large underdog. To further analyze this result, a second regression adds a dummy variable for if the home team is the favorite, but the parameter estimate is statistically insignificant, providing no support to the idea that fans prefer to attend matches where the home team is favored. A third regression using the brand strength of the away team gives a statistically significant positive result suggesting that the match uncertainty variable was largely picking up fan preference for attending games with popular away teams. These popular teams are also likely to be very good, which creates the result of increased attendance for more certain expected outcomes (in this case more certainty that the away team will win). These three different specifications do not change the significance or the general positive magnitude of the effect of seasonal uncertainty on attendance. These results provide support for the UOH at the seasonal level while also providing an illuminating explanation for previous European football studies that showed a U-shaped relationship between attendance and match-level competitive balance.

Berkowitz et. al. (2011) use both attendance and television broadcast data for the NASCAR Sprint Cup Series from 2007-2009 to test the UOH at the race (game) level and the individual season level. For race level uncertainty, the adjusted churn from Mizak et. al. (2007) is used in order to account for the amount of observed change between the pre-race starting grid and the final results. Unlike professional team sports where there is one winner and one loser in each game, Sprint Cup races have 43 drivers and each finishing position is important in the season long standings. As a result, uncertainty measures that strictly looked at the winner or top finishers of a race would be insufficient. For intra-seasonal uncertainty, the HHI of season performance points is used. The results from the attendance and viewership regressions show that seasonal uncertainty is a statistically significant predictor of both attendance and television ratings/viewers, with a lower concentration of points leading to greater attendance and viewership as predicted by the UOH. The race level uncertainty variable is statistically significant only for the television audience, with a greater churn (more competitive balance) leading to higher ratings and viewership. These results make sense because television viewers have low switching costs and can easily change the channel if a race is uninteresting for any reason (including a lack of competitive balance). However the choice to attend a race is made well in advance and therefore should not be affected by within-race outcomes such as the adjusted churn. These results provide strong support for the UOH for both attendance and television viewership in NASCAR.

Schmidt and Berri (2001) use Gini coefficients of wins (in one-year, three-year, and five-year lags) as explanatory variables in an MLB aggregate attendance model from 1901-1999. The results show that within-season and across-season competitive balance are both statistically significant drivers of the aggregate attendance of both the AL and NL. For example, the estimate on the one-year lag Gini coefficient (within-season balance) suggests that moving from the current level of competitive balance to the historical low would lead to an attendance reduction for each AL team of 79,696 and for each NL team of 32,151 while moving to the historical high would lead to an attendance increase for each AL team of 38,031 and for each NL team of 22,084.

Krautmann and Hadley (2006) test the UOH in MLB from 1950-2003 using an intra-seasonal competitive balance measure (the ratio of actual to idealized standard deviation of win percentages) and an inter-seasonal competitive balance measure (the

Markov transitional probability of a playoff team from the previous season qualifying for the playoffs again in the current season). The results from the attendance regression show that although increased within-season competitive balance increases attendance, the effect is not statistically significant. Increasing inter-seasonal competitive balance, on the other hand, has a statistically significant positive effect on attendance, although breaking the data up into AL and NL shows that the effect is only present for the AL. In that case, increasing inter-seasonal competitive balance by one standard deviation is expected to increase attendance per game by 424. Lee and Fort (2008) find the opposite results concerning the effect on MLB attendance of within-season and across-season competitive balance measures. Using data from 1901 to 2003 it is shown that seasonal uncertainty (as measured by the average difference in win percentage between division winners and second place finishers) had a statistically significant effect on league-wide attendance in support of the UOH. The consecutive season uncertainty measure (the correlation between each team's winning percentage and its previous three year average) was not statistically significant.

Tainsky and Winfree (2010) estimate a game-level attendance demand model in MLB using data from 1996-2009 and eight different measures of uncertainty of outcome: one game level, five seasonal, and two inter-seasonal. Of particular interest are four seasonal measures that involve the probability of qualifying for the playoffs, and thus extensive Monte Carlo simulations are used to simulate seasons such that playoff probabilities can be forecast at the point of each individual game. The results from the attendance model show that six out of eight of the uncertainty variables are statistically insignificant. The two that are significant are the marginal impact of a win on the probability of making the playoffs (seasonal uncertainty) and the change in home team win percentage compared with the end of the previous season (inter-seasonal). The first result has a positive sign as expected, which suggests that later season games for playoff contending teams are likely to drive increased attendance. However, the second result has a negative sign which suggests that if the home team is worse than the previous season, attendance will rise. This result, in combination with the fact that the parameter estimate on the ticket price control variable was positive and statistically significant, suggests that the model may have some problems and the results should be taken with caution.

Krautmann et. al. (2011) use a monthly attendance demand model for MLB in order to further understand the effects of all three forms of competitive balance on attendance over the course of a season. The competitive balance measures are Lee's (2004) tail likelihood metric (game level), Lee's (2009) league seasonal uncertainty variable, and Humphreys' (2002) CBR (inter-seasonal). Using data from 1957-2006, the results show that seasonal uncertainty is a statistically significant determinant of monthly attendance for both leagues but only in September, the last month of the season when the playoff chase is in full swing. The magnitude of this effect is greater for the NL than for the AL, where the observed 50% increase in seasonal uncertainty over the sample period would be expected to increase the attendance per game in September by 1,582 in the NL and 819 in the AL. The results for game uncertainty were almost always statistically insignificant regardless of the month or the league, while the results for CBR were often significant, but the sign on the estimate varied across the months and leagues. These results suggest that for MLB, the UOH may only be significant for late season games in regards to seasonal uncertainty.

Although a few of the UOH studies reviewed in this section also contained ACB research, the vast majority of studies focus either on ACB or UOH analysis. Of those that do include both ACB and UOH work, they all begin with the analysis of competitive balance before moving on to empirical tests of the uncertainty of outcome hypothesis. This approach may stem from the natural progression from theory to empirical tests, where ACB (though empirical) represents a closer tie to the theoretical modeling of professional sports leagues. However, thinking of competitive balance research as beginning with ACB and moving on to UOH is misguided. UOH research informs which (if any) forms and measures of competitive balance are significant drivers of fan interest in the form of attendance and/or television ratings. Only with this information should scholars then move to ACB research to determine whether these forms and measures of competitive balance have changed over time and in response to institutional changes. This way, any ACB findings will be practically meaningful in terms of their effect on fan interest as originally theorized by Rottenberg (1956).

2.4 Summary of Literature and Future Directions

The previous competitive balance literature review has shown that the research in this area can be divided into three main branches: theoretical modeling, analysis of competitive balance (ACB), and uncertainty of outcome hypothesis (UOH). The majority of theoretical models, especially recently, have focused on the impacts of various forms of revenue sharing on competitive balance, with the conclusions being highly dependent on the underlying economic assumptions regarding the league in question. The ACB line of research has largely focused on measuring seasonal levels of competitive balance while the UOH line of research has mainly focused on determining the attendance response to match-level competitive balance. Within both streams of literature, the results are often mixed due to the different specific competitive balance measures used as well as potential differences in the league structure or fan base of different leagues. For example, within the match-level UOH literature stream, the conflicting results can perhaps be attributed to the fact that in the United States, fans prefer competitively balanced outcomes at the match-level as predicted by the UOH, whereas in Europe fans indirectly prefer unbalanced outcomes due to their interest in attending games where either the home or away team is one of the perennially popular and successful teams (e.g. Manchester United in the English Premier League).

Other seemingly conflicting results from both ACB and UOH research can be explained by more clearly defining what level of competitive balance is being considered: match, seasonal, consecutive season. For example, the conclusions using one measure of seasonal competitive balance in terms of how it has changed over time (ACB) or how attendance changes in response to its varying levels (UOH) may not be the same for a given measure of consecutive season competitive balance. In consideration of the fundamental differences between these three levels of competitive balance, scholars should seek to include various balance measures accounting for multiple levels (Fort 2006), or should focus on under-studied areas such as consecutive season uncertainty for both ACB and UOH research streams.

Another significantly under-studied area of competitive balance research centers on playoff outcomes. Longley and Lacey (2012) point out that almost all previous competitive balance studies look at regular season outcomes only and completely ignore the results of playoffs. However, from a fan perspective, playoff outcomes are likely more important than the regular season as the playoffs determine the championship. To that end, fans likely characterize a team with the best regular season record that loses in the first round of the playoffs as a failure, but a team with a 0.500 regular season record that wins the playoffs as a success. As a result, Longley and Lacey consider the effect of the playoffs on competitive balance, with the finding that a playoff system, in and of itself, should increase competitive balance by replacing the outcome of a long, play against the field regular season that is prone to reveal true underlying team quality with the outcome from a short, head-to-head series of matches with a greater chance of upsets. Furthermore, it is shown that decreasing the number of games in each playoff series as well as changing the playoff pooling structure from league to conference to divisional will increase the frequency of upsets and the corresponding level of competitive balance.

Using data from the NHL and NBA from 1994-2004, Longley and Lacey show that regular season league champions made the final championship series in the playoffs just 25% (NHL) and 60% (NBA) of the time, emphasizing the reshuffling nature of the playoffs. In addition, the correlation between playoff games won and team payroll is substantially lower in the NHL than the correlation between regular season win percentage and payroll during this time period. Lastly, the HHI of teams finishing in the top-8, top-4 and top-2 of the regular season NHL standings are higher than the corresponding HHI of teams making the round of 8, round of 4, and Stanley Cup finals, showing a greater level of turnover of teams across seasons in regards to playoff outcomes as opposed to regular season outcomes. All of these observations support the idea that playoff systems dramatically change final outcomes as compared to regular season standings and therefore playoff structures and results warrant further consideration in studies on competitive balance.

The only previous study that specifically looks at how changing playoff structures affect competitive balance and the corresponding fan response is by Lee (2009). Using a seasonal uncertainty measure that accounts for the relative standing of every team in a given league-year, Lee shows that the level of competitive balance has a general positive trend in MLB from 1901-2006. Breaking the sample up into three periods based on the number of teams that qualified for the playoffs each year (1901-1968, two teams; 1969-1993, four teams; 1994-2006, eight teams) shows that there is a statistically significant increase in the level of uncertainty for each league as the number of playoff teams is increased. Furthermore, this increase in uncertainty leads to a statistically significant increase in league-wide attendance. As a result, by increasing the number of teams that qualify for the playoffs in 1969 and 1994, MLB was able to increase the level of seasonal competitive balance which directly led to increased attendance. The 1969 postseason restructuring increased AL attendance by 271,253 and NL attendance by 137,256 per year while the 1994 restructuring increased AL attendance by 143,764 and NL attendance by 237,233 per year. This study provides strong empirical evidence of the importance of playoff structure on competitive balance. However, as just a single study in this area, it is limited in that it only looks at the seasonal level of balance and only uses data from MLB. A significant opportunity therefore exists to investigate the UOH using consecutive season uncertainty measures and to determine how these measures are impacted by a league's choice of playoff structure such as the number of teams that qualify for the playoffs each year.

CHAPTER 3

CONCEPTUAL FOUNDATION AND HYPOTHESES DEVELOPMENT

In consideration of the previous competitive balance literature review, it is clear that uncertainty of outcome remains an important and unsettled research area with two significant gaps in the literature: playoff structure/outcomes and consecutive season competitive balance measures. Almost all previous studies ignore the issue of the playoffs entirely, which is a serious limitation as playoff structure and outcomes have been shown to be important elements that impact the competitive balance of a league (Longley and Lacey 2012). Similarly, the vast majority of UOH studies are focused on game and seasonal levels of competitive balance, which may not represent the level of competitive balance to which fans are most interested. This dissertation seeks to add to the literature in these two important areas by investigating the effect of playoff structure (measured by the number of teams qualifying for the playoffs) and consecutive season competitive balance (measured by playoff churn) on league-wide attendance.

One way to break down the conceptual foundation of competitive balance research is put forth by Szymanski (2003) in his essay summarizing the theoretical importance of maintaining competitive balance in professional sport leagues:

Claim One: Inequality of resources leads to unequal competition

Claim Two: Fan interest declines when outcomes become less uncertain (UOH)

Claim Three: Specific redistribution mechanisms produce more outcome uncertainty

The first of these claims is usually taken as a given, with monopoly territorial rights serving to foster underlying differences in revenue generating potential between large market and small market teams. In this situation, large market teams find it more financially rewarding to secure additional playing talent as compared to small market teams, leading to potential concerns about a lack of competitive balance. Szymanski empirically supports this notion by showing a statistically significant relationship between team payrolls and winning percentage for all of the leagues studied: MLB, NFL, NBA, NHL, and the top soccer league in each of England, Italy, Germany, and Spain.

Other studies looking at the relationship between market size and winning percentage in MLB include Schmidt and Berri (2002), Gustafson and Hadley (2007), and Lewis (2008). Schmidt and Berri use three different categories of variables to define market size (metropolitan statistical area measures, revenue measures, and expenditures), and find that most of the revenue and expense variables have a statistically significant positive relationship with winning percentage. The authors caution that although higher revenues/payrolls may induce greater winning, it is also possible that high winning percentages enable teams to earn greater revenues and spend more on payroll. Gustafson and Hadley use a four-equation simultaneous model of win percent, team payroll, team total revenue, and team local revenue to show that market size has a statistically significant positive effect on local revenue. This in turn leads to increased payroll, which has a statistically significant positive effect on win percentage. However, the authors caution that the effect of market size on winning percentage is relatively small, with each additional one million in market population expected to yield an additional 0.233 to 1.126 additional wins per season, depending on the exact specification used. Lewis uses a structural dynamic programming model to analyze payroll investment decisions by MLB team owners from 1976-2006, finding that market population has a statistically significant impact on the value of a team's payroll investments. As a result, the optimal payroll for a given team rises with its market size such that, for example, a team's optimal payroll doubles as market size increases from 2.5 to 7.5 million. Coupled with the correlation between team payroll and on-field success, this analysis adds validity to the economic foundation of unequal market sizes leading to competitive imbalance.

Although the previous studies offer some caveats to the findings, overall there seems to be a fairly broad consensus in support of the first competitive balance claim put forth by Szymanski (2003). Teams with a larger home market will have greater marginal revenue per win at a given winning percentage than their small market peers. As a result, large market teams will spend more on payroll, earn more revenue, and have higher winning percentages than small market teams, a competitively unbalanced outcome due to the underlying differences in market size that are protected by monopoly territorial rights. Since some level of competitive imbalance is thus shown to be rooted in the structure of the leagues themselves, it then becomes important to consider Szymanski's (2003) second and third claims: does this lack of competitive balance lead to lower fan interest as predicted by the UOH and therefore necessitate institutional changes to improve balance?

3.1 Playoff Structure UOH Hypothesis

The first question this dissertation seeks to address in regards to the UOH is whether playoff structure (in terms of the number of teams that qualify for the playoffs in a given year) can affect competitive balance in a way that impacts league-wide attendance. Numerous other studies have investigated whether leagues can enact institutional changes to address competitive imbalance problems in order to restore the level of balance to a point at which consumer interest in the league is maximized. One of the most important institutional structures meant to foster competitive balance (at least as argued by the owners) was the reserve rule. The implementation of free agency in MLB in 1976 provides a natural test for the efficacy of the reserve rule in terms of promoting competitive balance. However, the results from 20 studies as reviewed by Szymanski show seven finding no change in competitive balance post-free agency, nine finding an improvement, and four showing a reduction. Thus, support for the reserve clause as a tool to enhance competitive balance is very mixed. Other institutional rules meant to promote competitive balance that have been studied by academic scholars include the reverse order draft (e.g. Grier and Tollison 1994), salary caps (e.g. Lee 2010), luxury taxes (Dietl et. al. 2010), and various forms of revenue sharing (e.g. Fort and Quirk 1995; Kesenne 2000a; Miller 2007). Overall, the theoretically and empirically observed result of most of these rules is either no change or an ambiguous effect on competitive balance (Sanderson and Siegfried 2003). Nevertheless, professional sport leagues, in the name of improving competitive balance, have continued to implement new forms of payroll caps, luxury taxes, individual salary caps, and revenue sharing that may not have any effect on competitive balance at all.

Sanderson and Siegfried (2003) argue that the one change most likely to induce competitive balance in sport leagues is to allow franchises to move from small markets to larger markets such as New York City to even the revenue generating potential of teams. However, all of the major U.S. professional sport leagues (unlike those in Europe) have restrictions on franchise movement to protect the local monopolies of team owners.

Sanderson (2002) discusses how small changes to the structure of the competition itself, unlike the large changes to the economic structure of a league, can significantly affect outcomes and the level of competitive balance. This is seen in qualifying times that reward better competitors with either a head start (car racing) or a preferable/faster lane assignment (swimming). Seeding in tennis and in the playoffs for the four major professional leagues also confers the advantages of home-field and of playing against a weaker opponent. In addition, the number of playoff games per series greatly affects the chances that the weaker opponent will pull off the upset, with single game playoffs in the NFL and college football and basketball promoting greater uncertainty as compared with the mostly best of seven series in MLB, the NBA and the NHL. This result, along with the specifics of how teams are pooled for the playoffs (by conference, by division, etc.) is empirically shown to significantly affect playoff outcomes by Longley and Lacey (2012). Lastly, a simple change that leagues can implement to affect the level of competitive balance is to increase the number of teams that qualify for the playoffs (Sanderson 2002; Sanderson and Siegfried 2003). Such a change can significantly reduce the likelihood of repeat champions/dynasties. These and other institutional rule changes over the years in all of the major professional sports can have as much or a greater effect on competitive balance than the many financial restrictions such as revenue sharing, luxury taxes, and salary caps that have been fought for in the name of promoting balance. In recognition of these ideas, attention now turns to how a league's playoff structure can affect competitive balance and attendance. No empirical study thus far has analyzed the historical differences in the percent of playoff qualifying teams within and across leagues in terms of competitive balance and the corresponding effect on league-wide attendance.

Within and across leagues, the number of teams that qualify for the playoffs each year has varied considerably. In MLB and the NFL, the leagues began with no playoffs and slowly added to the number of playoff teams first with a single championship game/series (two playoff teams) and now to the point where there are 10 playoff teams in baseball and 12 in football. In both these leagues, the number of teams qualifying for the playoffs has increased over time from 0% in their early history to their current points of 33.3% and 37.5% respectively. The opposite situation is true for the NHL and NBA, where the percentage of teams qualifying for the playoffs started much higher, and has slowly decreased over time through league expansion. In both of these leagues, the percentage of teams that currently make the playoffs each year is at a nearly historic low of 53.3% compared to previous maximums of 80.0% in basketball and 85.7% in hockey (see Appendix A).

The history of the number and percentage of teams that qualify for the postseason is the simplest in MLB. Starting in 1903, a playoff structure was created where two of the 16 MLB teams (12.5%) qualified for the World Series. This exact format remained in place through 1960, at which point MLB started expanding the number of teams in the league, first to 18, then to 20, then to 24. When the league first reached 24 teams, in 1969, the number of playoff teams was doubled to four (16.7%). In 1995, with 28 teams in the league, the number of playoff teams was again doubled to eight (28.6%). Finally, in 2012, an additional two teams were added to the playoffs so that ten out of the 30 teams qualify for the playoffs each year (33.3%). The same general history is observed in the NFL, with the first 2-team playoff (NFL championship game) starting in 1933 when there were ten teams in the league (20.0%). Over the next 45 years, the NFL experienced small contractions and expansions in the number of teams in the league, but the number of playoff teams remained at two. By 1967, with 16 teams in the league, the number of playoff teams was doubled to four (25.0%), and in 1970, following the AFL-NFL merger that brought the number of NFL teams up to 26, the playoff field was again doubled to eight (30.8%). Since the merger in 1970, the NFL has slowly continued to expand the number of teams in the league while also increasing the number of playoff teams to 10 in 1978 (35.7%) and to 12 in 1990 (42.9%). Since 1990, the number of teams in the NFL has increased from 28 to 32 while the number of playoff teams has remained at 12 (37.5%).

The history of the number and percentage of playoff qualifying teams in the NHL and NBA is slightly more complicated. In the early history of the NHL (1918-1942), the number of playoff teams increased from two to six while the number of teams in the league fluctuated between three and ten with various contractions and expansions. From 1943-1967 (the era of the Original Six), there were six teams in the league, four of which qualified for the playoffs (66.7%). In 1968, both the number of teams in the league and the number of playoff teams doubled (to 12 and 8, respectively), keeping the percentage at 66.7%. By 1975, the number of teams in the NHL had increased to 18, but the number of playoff teams was correspondingly increased to 12, such that the playoff percentage remained at 66.7%. In 1980, with 21 teams in the league, the number of playoff teams was further increased to 16 (76.2%). Since that time, the number of playoff teams has remained at 16 while the NHL has experienced incremental expansion to the point where there are now 30 teams in the league and the percentage of playoff qualifying teams has been reduced to 53.3%. In the early history of the NBA (1947-1974), the number of playoff qualifying teams alternated between six and eight while the number of teams in the league fluctuated between eight and 17. In 1975, with 18 teams in the league, the number of playoff teams was increased to 10 (55.6%) and in 1977, with 22 teams in the league, the number of playoff teams was further increased to 12 (54.5%). The number of playoff qualifying teams was increased to 16 in 1984 and has remained there since, despite expansion that brought the number of NBA teams from 23 in 1984 (69.6%) to 30 today (53.3%).

Looking over these histories, it is clear that all four leagues have generally increased (decreased) the number of playoff qualifying teams in line with league expansion (contraction). However, a few observations in each league do not fit that general mold. In MLB, the number of playoff teams was doubled from four to eight in 1995 despite no change in the number of teams. This move thus doubled the percentage of playoff teams from 14.3% to 28.6%. Similarly, in the NFL, from 1976-1994 the number of teams in the league remained constant at 28 while the number of playoff teams was increased from eight to ten in 1978 and then from ten to 12 in 1990. These moves increased the percentage of playoff teams from 28.6% to 35.7% and then to 42.9% (the historical high point for the NFL). In the NBA and NHL, the number of playoff teams has remained at 16 in each league since the early 1980s despite significant expansion during this time that saw the number of NBA teams increase from 23 to 30 and the number of NHL teams increase from 21 to 30. This lack of playoff expansion has caused the percentage of playoff qualifying teams to fall from 69.6% to 53.3% in the NBA and from 76.2% to 53.3% in the NHL. Assuming that leagues choose the number of playoff teams in order to maximize league revenues, these observations across the four major professional sport leagues in the U.S. suggest that the optimal percentage of playoff-qualifying teams in terms of maximizing league attendance falls somewhere in the range of 30-50%.

A league's choice of the percentage of teams that qualifies for the playoffs is influenced by two competing effects. On the one hand, increasing the number of teams that qualify for the playoffs could increase fan interest insomuch as more teams will still be in the hunt for playoff spots as the season progresses. In the early history of MLB and the NFL, when there was just a single championship game/series or even no championship game at all, it can be expected that teams that quickly fell behind in the regular season standings suffered from low attendance for the remainder of the season as fans rightfully gave up on the team's chances for that season. By increasing the number of qualifying teams in these leagues, it can be expected that more teams were competitive in terms of securing a playoff spot, increasing overall fan attendance in a given year (e.g. Lee 2009; Krautmann et. al. 2011). On the other hand, increasing the number of playoff teams shifts the importance from the regular season to the playoffs, which could negatively affect regular season attendance as fans wait until the "real" season begins in the playoffs. This notion can clearly be observed in the extreme case where the percentage of teams qualifying for the playoffs approaches 100%, completely deteriorating the significance of the regular season and likely leading to a drastic reduction in regular season attendance. The general fan utility function can then be written as:

Fan utility U = f(*competitiveness for playoff qualification*, *regular season importance*, game characteristics, team characteristics, league characteristics, market characteristics, other factors)

These two competing effects on attendance of increasing the number of teams that qualify for the playoffs are apparent in the vastly different playoff structures of NCAA Division 1 football and basketball.

For nearly the entire history of major college football, there was no formal playoff system to determine a champion. When the Bowl Championship Series (BCS) was introduced in 1998 to match the top two teams at the end of the regular season in a national championship game, it was a major step forward in that it essentially created a two-team playoff. Although financially successful, the BCS became loathed by fans for its limitations: only two of the more than 120 top level college football teams qualified for the playoff each year, leaving the vast majority of college football teams unable to contend for a championship, including some that were undefeated. Despite these persistent fan criticisms, the NCAA only recently decided to expand the playoffs to a mere four teams in 2014, citing the need to maintain the importance of the regular season (Russo 2012). In contrast, the playoff system in division 1 basketball began in 1939 with eight teams, and has consistently expanded over time to where it now includes 68 (out of more than 340) teams each year. Although this NCAA basketball tournament (deemed March Madness) is regularly considered the most exciting collection of collegiate athletic games of any sport, the inclusiveness of such a large percentage of teams has potentially destroyed fan interest in the regular season (Bishop 2012). If fans of big name teams know that their team is essentially guaranteed to qualify for the postseason tournament, then regular season games could lose their value. On the other hand, this greater inclusiveness of teams could increase uncertainty and attendance for the hundreds of teams on the bubble that realistically have hope of qualifying for the tournament as the regular season winds down.

This dissertation seeks to determine which of these two competing effects on attendance of increasing the number of teams to qualify for the playoffs is greater. If the effect of greater inclusiveness creating greater uncertainty dominates, then it is expected that increasing the number of playoff teams will increase attendance. Conversely, if the effect of shifting importance from the regular season to the postseason dominates, then it is expected that increasing the number of playoff teams will decrease attendance. If these two competing effects are equal and opposite, then no effect on attendance will be observed.

H1: Increasing the percentage of teams that qualify for the playoffs will affect league-wide regular season attendance based on which of two competing effects is larger: more inclusiveness creating more uncertainty of outcome, or the shift of importance from the regular season to the postseason.

3.2 Consecutive Season UOH Hypothesis

The second question this dissertation seeks to address in regards to the UOH is whether consecutive season competitive balance (as measured by the churn in qualifying and advancing playoff teams each year) impacts league-wide attendance. Although there has been a considerable amount of research in this general area as highlighted by the UOH literature review in the previous section, the results have been mixed. Szymanski (2003) finds that of the 22 pre-2003 UOH studies, 10 showed strong support for the UOH, seven offered weak support, and five contradicted it. The mixed nature of these findings is not surprising considering that each study did not utilize the same general type of uncertainty amongst the three accepted levels of competitive balance: match, seasonal, and consecutive season. In addition, even studies using the same level of competitive balance often make use of different specific measures of that type of competitive balance which complicates the comparison across studies. Some of these various competitive balance metrics have also been shown to suffer from certain measurement issues, including Gini coefficients (Utt and Fort 2002; Mizak et. al. 2005), pre-game betting odds (Dawson and Downward 2005), league standings (Dawson and Downward 2005), standard deviation of win percentages (Mizak et. al. 2005), HHI of wins (Owen et. al. 2007), ratio of actual to idealized standard deviation of win percentages (Owen 2010), and concentration ratios (Manasis et. al. 2011).

In light of these many differences, conflicting results, and measurement issues, the field could benefit greatly from the identification of a single competitive balance measure to which consumers show the greatest sensitivity (Zimbalist 2002; 2003). Although UOH studies are dominated by game-level analysis and ACB studies have largely focused on seasonal measures, neither of these levels of competitive balance likely describe what fans are most interested in concerning uncertainty of outcome. This can be seen by the fact that fans considered competitive imbalance to be a significant problem in Major League Baseball during the 1990s (Rogers 2001), yet academic studies have consistently found increasing levels of competitive balance in MLB over time, including through the 1990s. This difference is likely accounted for by the fact that studies of competitive balance in MLB have largely focused on seasonal measures (e.g. Quirk and Fort 1992, Butler 1995, Schmidt and Berri 2001) with one recent study investigating league-wide game-level measures (Bowman et. al. 2013). In all of these studies, the finding of increased levels of competitive balance over time is clearly not appreciated by MLB fans, who lamented the repeated dominance of the Yankees during that decade. In a study commissioned by MLB in 2000 (deemed the Blue Ribbon Report) to investigate various economic issues including competitive balance, it was shown that teams in the top 25% of payrolls won all of the World Series games from 1995-1999 and that teams in the top 50% of payrolls won all of the playoff games during this time (Levin et. al. 2000). The Blue Ribbon Report concludes that MLB's competitive balance problem is rooted in inter-seasonal concerns and that "proper competitive balance will not exist until every well-run club has a ***regularly recurring reasonable hope of reaching postseason play***" (Levin et. al. 2000, pg. 5, emphasis in original). This idea of the type of competitive balance to which fans show the most interest contrasts with the game-level and seasonal aspects that have largely been the focus of academic inquiry to date. In fact, several studies in response to the Blue Ribbon Report have suggested that MLB is incorrect in asserting that it has a competitive balance problem (e.g. Schmidt and Berri 2002). These studies mistakenly ignore the fact that even if seasonal measures of competitive balance show greater balance, consumers may be more interested in and sensitive to changes in inter-seasonal balance. As a result, UOH studies should focus on these inter-seasonal aspects of competitive balance under the premise that fans are most responsive to that level of balance. This sentiment is echoed by Humphreys (2003a) in his call for a multi-season approach to future competitive balance research.

The first study to specifically highlight the limitations of within-season measures of competitive balance was Eckard (2001). In particular, it was shown that two seasons with the exact same level of seasonal balance could have shown either no change in league standings or a complete re-ordering of all teams top to bottom. These two cases represent the extremes of the amount of inter-seasonal balance present in the league, but traditional measures of within-season balance would treat these two leagues identically. As a result, Eckard proposed a new measure of balance that involved decomposing the variance of win percentages into within-season and across-season components. The drawback of this measure is the difficulty of interpreting the relative values of the two components of the variance decomposition. Humphreys (2002) was the next to propose a new inter-seasonal competitive balance measure, the CBR. Although the CBR was later shown to be conceptually identical to Eckard's (2001) variance decomposition (Eckard 2003), the CBR still has the practical advantage of being a single number (Humphreys 2003b). More recently proposed measures of consecutive season competitive balance include Markov transitional probabilities (Hadley et. al. 2005), the adjusted churn (Mizak et. al. 2007), the normal density function of games back (Lee 2009), and the mobility gain function (Lenten 2009a). All of these inter-seasonal measures offer the advantage of providing information that is likely at the root of fan interest in sport leagues. However, with the exception of Markov transitional probabilities, these measures reflect regular season outcomes only.

Although important, the regular season is just one component of a sports league, with the playoffs serving as a “second” season in the determination of league champions (Longley and Lacey 2012). Any inter-seasonal competitive balance measure that doesn’t include playoff outcomes ignores the source of greatest potential fan interest in professional sport leagues. Playoff games in the Big Four leagues regularly have significantly higher television ratings as well as sold out attendance despite substantially higher ticket prices. As a result, the search for a “best” measure of competitive balance in line with Zimbalist’s (2002; 2003) proposition should include some measure of playoff success. Although various competitive balance studies have looked at the playoffs in one form or another, the specific use of the qualification for and advancement in the playoffs as a measure of consecutive season uncertainty is currently lacking in the competitive balance literature. The closest previous example is the use of Markov transitional probabilities as a measure of the qualification for the playoffs, but only one study (Krautman and Hadley 2006) utilized this measure in a test of the UOH. The results from this study provide statistically significant support for the UOH using Markov transitional probabilities as the measure of inter-seasonal uncertainty, in line with the idea that fans care about competitive balance in regards to the playoffs.

In terms of playoff advancement, several studies have investigated championship outcomes (e.g. Cairns 1987; Scully 1989; Quirk and Fort 1992; Fizel 1997; Dittmore and Crowe 2010), but none of these studies used this information in a test of the UOH. The combination of just one UOH study measuring playoff qualification and no UOH studies measuring playoff advancement and championships highlights an important gap in the competitive balance literature. Namely, fans are most sensitive to inter-seasonal measures of uncertainty of outcome and in particular respond to which teams qualify for and advance through the playoffs each year. If the same small subset of teams regularly qualifies for and advances to later rounds of the playoffs (representing a low level of churn), fans could have reduced interest in the league due to a perceived lack of inter-seasonal competitive balance. On the other hand, fans may have a preference for historically strong teams and dynasties. If that is true, then lower playoff qualification/advancement churn should yield greater attendance. Similarly, fans may have a taste for fairness, and desire that the regular season champion is rightfully crowned as the champion of the playoffs as well. In this case, the redistributive effects of a playoff tournament on regular season outcomes (Longley and Lacey 2012) would be looked upon unfavorably. The general fan utility function can then be written as:

Fan utility U = f(*consecutive season competitive balance*, *dynasties, perceived fairness of playoff outcomes*, game characteristics, team characteristics, league characteristics, market characteristics, other factors)

Whether fans respond positively or negatively to increased consecutive season competitive balance is therefore an open question, including whether fans are more sensitive to early playoff rounds (e.g. which teams qualify for the playoffs) or later playoff rounds (e.g. which team wins the championship). The inter-seasonal churn of teams in the early playoff rounds may be a more important driver of league-wide fan interest because these rounds consist of a greater number of teams and therefore may appeal to a broader group of a league's fan base. In addition, the playoffs can be an extremely lengthy process (especially in the NBA and NHL), and thus fan interest in outcomes may be maximized during the first round and then declining with each successive round as the novelty wears off. On the contrary, fans may be more sensitive to the inter-seasonal churn of teams in the later playoff rounds because each round in a playoff system becomes closer to and more important in determining the league champion. If fans primarily follow sport leagues in order to find out which team emerges as the champion each year, then it is expected that later playoff rounds (and their corresponding level of competitive balance year-to-year) will have a great effect on league-wide attendance.

Another factor that potentially will affect the relationship between consecutive season competitive balance and league-wide attendance is the time frame with which playoff churn is measured. The specific time frame during which fans might be most sensitive to changes in consecutive season competitive balance remains an empirical question, with possibilities ranging from using just the previous season, using a simple average of some number of previous seasons, or using a weighted average with greater weights for more recent seasons. Research in psychology and behavioral economics has consistently found the presence of the "recency effect," whereby people are cognitively biased toward more recent observations and experiences. In consideration of these findings, it is possible that only the most recently finished season is salient to fans in terms of their appreciation for the presence (or lack) of inter-seasonal competitive balance. However, the recency bias for fans may not be quite so drastic, with playoff results from two or more seasons ago still preserved in fan memory and influencing perceptions of the level of competitive balance. This dissertation seeks to answer these questions concerning the effect of various forms of playoff qualification/advancement consecutive season competitive balance measures on fan response in terms of league-wide attendance.

H2: Higher levels of inter-seasonal competitive balance as measured by the churn of playoff qualifying/advancing teams will affect league-wide regular season attendance in the direction consistent with fan preference for either competitive balance or dynasties/fairness. The magnitude and direction of this relationship will be impacted by both the round of the playoffs under consideration as well as the time-frame used for the measurement of playoff churn.

CHAPTER 4

DATA AND ANALYSIS METHODOLOGY

This chapter presents the methodology that is used to test the previously stated hypotheses. The first two sections describe the methodology for hypothesis one, that increasing the percentage of teams that qualify for the playoffs will affect league-wide regular season attendance based on two competing effects: more inclusiveness creating more uncertainty of outcome, and the shift of importance from the regular season to the postseason. The remaining two sections describe the methodology for hypothesis two, that higher levels of inter-seasonal competitive balance as measured by the churn of playoff qualifying/advancing teams will affect league-wide regular season attendance based on fan preference for either competitive balance or dynasties/fairness.

For hypothesis one, the regression model is described first followed by variable definitions and descriptive statistics. The variables used in the model are broken down into the dependent variable, the independent variables of interest, and the control variables. In each case, a justification for the choice of the variable(s) used in the analysis is presented, including a priori expectations of the results and a brief discussion of the descriptive statistics. For hypothesis two, the regression model is a simple extension of that for hypothesis one, with the same dependent variable and control variables. As a result, only the new independent variables of interest are defined and discussed.

4.1 H1 Model Specification

The following regression equation serves as the foundation for the analysis of the first hypothesis:

League-wide Attendance = Playoff Percent + Playoff Percent^2 + Control Variables

To capture the competing effects of increases (decreases) to the playoff percent creating more (less) uncertainty of outcome while also decreasing (increasing) the importance of the regular season, the playoff percent variable is modeled with both a linear and quadratic term. This allows for the effect on attendance of increasing the playoff percent to be positive for some range of playoff percentages while negative for others. This is consistent with the a priori expectation that attendance is maximized for some playoff percentage between 30 and 50%. The choice of control variables as well as the specific formulation of the dependent variable came from an iterative process (described in detail in section 5.4 Alternate Models) that was used to refine the foundational regression model into the final specification used for the analysis. Of particular importance was the need to use the average attendance per game (as opposed to the total league-wide attendance) as the dependent variable in order to eliminate multicollinearity problems and to use first differencing of all continuous variables in order to remove the non-stationary effects from the time-series data. Additionally, choices were made concerning the specific measurement of control variables within the six broad categories of controls used in this analysis: stadium capacity, stadium age, ticket prices, seasonal competitive balance, strikes/lockouts, and a trend. The final baseline first difference regression model used to test hypothesis one is shown below for MLB, the NHL, and the NBA:

MLB: AvgAttendPGFD(y) = PlayoffPctFD(x1) + PlayoffPct2FD(x2) +
AvgCapacityFD(x3) + RealTicketPriFD(x4) +
NewFranchise(x5) + Relocation(x6) + NewStadium(x7) +
CenSeasonCBFD(x8) + Strike72(x9) + Strike81(x10) +
Strike94(x11) + AttendTrendFD(x12) + error

NHL: AvgAttendPGFD(y) = PlayoffPctFD(x1) + PlayoffPct2FD(x2) +
AvgCapacityFD(x3) + RealTicketPriFD(x4) +
NewFranchise(x5) + Relocation(x6) + NewStadium(x7) +
CenSeasonCBFD(x8) + Lockout94(x9) + Lockout04(x10)
+ Lockout12(x11) + AttendTrendFD(x12) + error

NBA: AvgAttendPGFD(y) = PlayoffPctFD(x1) + PlayoffPct2FD(x2) +
AvgCapacityFD(x3) + RealTicketPriFD(x4) +
NewFranchise(x5) + Relocation(x6) + NewStadium(x7) +
CenSeasonCBFD(x8) + Lockout98(x9) + Lockout11(x10)
+ AttendTrendFD(x11) + error

Where each of the variables is defined as follow:

AvgAttendPGFD is the first difference of the average attendance per game, which is the total league-wide attendance divided by the total number of games for a given year.

PlayoffPctFD is the first difference of the percentage of teams that qualify for the playoffs in a given league-year.

PlayoffPct2FD is the first difference of the square of the percentage of teams that qualify for the playoffs in a given league-year.

AvgCapacityFD is the first difference of the average stadium capacity per game for a given league-year.

RealTicketPriFD is the first difference of the weighted average (by capacity) ticket price in real 2013 dollars for all teams in a given league-year.

NewFranchise is an integer value of the number of new teams added to a league through expansion prior to a given year.

Relocation is an integer value of the number of teams that relocated to a new city prior to a given year.

NewStadium is an integer value of the number of teams that completed construction of a new stadium or the extensive renovation of their old stadiums prior to or during a given year.

CenSeasonCBFD is the first difference of the ratio of actual to idealized standard deviation of win percentages calculated from the final standings for the middle one third of the teams in the league (33^{rd} to 67^{th} percentile).

Strike72 is a dummy variable for the strike-affected 1972 MLB season.

Strike81 is a dummy variable for the strike-affected 1981 MLB season.

Strike94 is a dummy variable for the strike-affected 1994 MLB season. Since the second half of the 1994 season (including the playoffs) was completely canceled as a result of this strike, the variable takes a value of 1 for the 1995 MLB season.

Lockout94 is a dummy variable for the lockout-affected 1994-95 NHL season.

Lockout04 is a dummy variable for the lockout-affected 2004-05 NHL season. Since this lockout led to the complete cancellation of the 2004-05 NHL season, the variable takes a value of 1 for the 2005-06 NHL season.

Lockout12 is a dummy variable for the lockout-affected 2012-13 NHL season.

Lockout98 is a dummy variable for the lockout-affected 1998-99 NBA season.

Lockout11 is a dummy variable for the lockout-affected 2011-12 NBA season.

AttendTrendFD is the first difference of the average attendance per game of the leagues not being considered in the current regression analysis. For the MLB regressions, AttendTrend is the average attendance per game of the NBA and NHL. For the NHL regressions, AttendTrend is the average attendance per game of the NBA and MLB. For the NBA regressions, AttendTrend is the average attendance per game of the MLB and NHL.

Descriptive statistics for the preceding variables can be seen below in Table 1 for MLB, Table 2 for the NHL and Table 3 for the NBA.

Table 1: MLB H1 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
AvgAttendFD	257.995	1420.455	-6243.26	4447.231
PlayoffPctFD	0.00336	0.035505	-0.15385	0.153846
PlayoffPct2FD	0.00154	0.016071	-0.07101	0.071006
AvgCapacityFD	19.57592	853.6060	-2545.65	2450.667
RealTicketPriFD	0.207008	0.780991	-1.19583	3.253435
NewFranchise	0.218750	0.723061	0	4
Relocation	0.171875	0.419928	0	2
NewStadium	0.578125	0.792919	0	3
CenSeasonCBFD	-0.018560	0.265180	-0.99945	0.638724
Strike72	0.015625	0.125	0	1
Strike81	0.015625	0.125	0	1
Strike94	0.015625	0.125	0	1
AttendTrendFD	178.4066	406.9994	-1582.26	923.7658

Table 2: NHL H1 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
AvgAttendFD	96.18279	669.2132	-3157.41	1158.866
PlayoffPctFD	-0.002720	0.034213	-0.09524	0.166667
PlayoffPct2FD	-0.003270	0.041823	-0.11791	0.194444
AvgCapacityFD	71.63129	260.9188	-543.563	1048.628
RealTicketPriFD	0.638761	3.814039	-11.4418	4.713594
NewFranchise	0.5	1.164965	0	6
Relocation	0.18	0.437526	0	2
NewStadium	0.48	0.973946	0	5
CenSeasonCBFD	0.004582	0.385923	-0.82870	1.051960
Lockout94	0.02	0.141421	0	1
Lockout04	0.02	0.141421	0	1
Lockout12	0.02	0.141421	0	1
AttendTrendFD	309.2832	782.9485	-2857.78	2313.191

Table 3: NBA H1 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
AvgAttendFD	265.0820	477.5770	-960.585	1667.847
PlayoffPctFD	-0.003740	0.043208	-0.13333	0.173913
PlayoffPct2FD	-0.004790	0.056	-0.19556	0.211720
AvgCapacityFD	150.2945	951.9855	-1954.96	3992.182
RealTicketPriFD	0.614593	3.541757	-8.92191	8.201990
NewFranchise	0.372881	0.848900	0	4
Relocation	0.338983	0.544888	0	2
NewStadium	0.762712	1.149797	0	7
CenSeasonCBFD	-0.002070	0.558573	-1.48559	1.498537
Lockout98	0.016949	0.130189	0	1
Lockout11	0.016949	0.130189	0	1
AttendTrendFD	222.5182	883.9129	-3071.81	2698.253

Looking at Tables 1-3, the descriptive statistics match expectations. Although the large magnitude of the standard deviation for each variable relative to its mean may look troublesome, this is a first difference model so these variables are measures of the changes in the absolute variables each year. As a result, the mean values are generally expected to be around zero, with both positive and negative changes throughout the data set leading to the relatively high standard deviations. In addition, the statistics are generally consistent across leagues, with each league showing a small increase in average attendance, average stadium capacity and real ticket prices over time. These trends support the observation that professional sport leagues have become more popular over time. One important difference between the leagues is that the percentage of teams making the playoffs has shown a slight increase over time for MLB, but a slight decrease for the NBA and the NHL. However, this is consistent with the discussion of the history of the percentage of the teams that qualify for the playoffs in each of these leagues (see Chapter 3).

The NFL is not included in this analysis because of the large number of sellouts that exist throughout the data set and which complicates the use of attendance figures as an accurate measure of demand. Although sellouts exist sporadically for each of the other three leagues, the frequency and magnitude are small enough that the aggregate league-wide attendance measure is expected to accurately model the true total demand. In recognition of the fact that the demand for professional sports boomed in the post World War II period in the United States (and thus likely exhibits different underlying relationships than the period prior), the analysis is limited to this time frame. Coupled with some attendance data limitations for the early years of the NBA and NHL, each data set therefore consists of the following years: MLB (1950-2013), NBA (1954-2013), and NHL (1964-2013). See Appendix B for a discussion of the data sources used in this study.

4.2 H1 Research Variables

The following subsections describe the type and definition of variables that are included in the final H1 regression model detailed in the previous section.

4.2.1 Independent Variables

Playoff Percent. The percentage of teams in a given league that qualify for the playoffs in each year, as calculated by dividing the number of available playoff spots by the total number of teams in that league for a given year.

Playoff Percent Squared. The square term of the playoff percent variable. In combination, these two independent variables are utilized to determine the effect of playoff structure on league-wide attendance as a test of Hypothesis 1. It is expected that the playoff percent will affect attendance in a quadratic nature, with attendance maximized for some playoff percent between 30 and 50%.

4.2.2 Dependent Variable

Average Attendance per Game. The league-wide regular season attendance for each league-year divided by the total number of regular season games played that year. Total league-wide attendance is the measure of aggregate consumer demand for a given professional sports league. Although this is an imperfect measure due to infrequent sellouts and misreporting, it is regularly used and accepted in both the sports economics literature as well as the broader economics literature as a good proxy of demand and league profitability (e.g. Schmidt and Berri 2004).

Alternate potential specifications for the dependent variable could look at team-level attendance and/or complete season attendance (regular season plus postseason). Postseason attendance is not considered in this analysis for two primary reasons. First, postseason games are nearly always sold out which means the attendance figures will be the home team's stadium capacity, which varies considerably across teams. This is problematic because the specific set of teams that qualify for the playoffs each year is largely random, and therefore the observed postseason attendance will be pre-defined by the playoff qualifying teams regardless of the overall fan interest in the league for a given year. In addition, the playoffs represent only a subset of the total teams in the league, which means the inclusion of the postseason attendance would bias the results toward specific teams and away from a collective league analysis. As a result, postseason attendance is a poor relative measure of fan interest in a professional sports league.

Second, even if postseason attendance was a good measure of fan interest in a league, it's likely that including this data would not have a significant effect on the analysis due to the limited number of playoff games. In MLB, even at the current historical high of 33% percent of teams making the playoffs, there is a maximum of just 43 playoff games in one year. This represents just 1.8% of the 2,430 regular season games played each season. In the NHL and the NBA, the current maximum number of playoff games in one year is 105, which is just 8.5% of the 1,230 regular season games played each season. In all three leagues, the effect of including postseason attendance is therefore likely to be small.

Team-level attendance is not considered for this analysis due to the overarching research question of investigating the effect of competitive balance on the league as a whole. Numerous previous studies (e.g. Borland 1987) have investigated the effect of various competitive balance metrics on individual team attendance. Not surprisingly, significant results have been found showing that the more competitive a given team is for a playoff spot, the higher the attendance will be for that team. However, these studies ignore the issue of whether the gain in attendance by these teams is offset by a potential drop in attendance of teams that have already clinched a playoff position or are hopelessly out of the playoff picture. From a league perspective, it is insufficient to note that a tighter playoff race will increase the attendance for those teams that are involved, without fully understanding the effect on all of the teams collectively. For this reason, it is important to measure league-wide attendance in order to adequately determine the overall effect of changes in competitive balance (such as the percentage of teams that qualify for the playoffs) on fan demand for the entire league. The league office would not be interested in enacting structural changes that led to an increase in fan interest for a given subset of teams if it came at the expense of reducing interest in the league as a whole. Only by investigating attendance responses at the league level can it be determined that a given variable collectively imparts a positive or negative effect on the entire league.

4.2.3 Control Variables

Control variables are utilized in the analysis to account for additional factors that could impact league-wide attendance for a professional sport league. The following control variables listed below were included in the analysis.

Average Real Ticket Price. A standard demand model suggests that the quantity of tickets demanded (attendance) will be inversely related to the price of the tickets, and therefore the average ticket price for each league in each year should be included as an important control variable. Unfortunately, information on average ticket prices in each league is limited and therefore most previous longitudinal studies do not include ticket prices in their models. Full data on average ticket prices is only available from 1952 in MLB, 1992 in the NBA, and 1995 in the NHL. Because of these limitations, tests using the entire dataset for the NBA and NHL will not be able to use ticket prices as a control variable. Instead, robustness tests are performed on subsets of the data that contain full ticket price information in order to validate the findings from the full model. Nominal average ticket prices for each year are converted into real 2013 dollars using the Consumer Price Index.

New Franchises. Increasing the number of teams in a league through expansion is likely to have an effect on average demand for games. On the one hand, creating more teams may open up new markets with strong pent-up demand (as well as national appeal) that contributes to an overall increase in the average attendance per game at the league level. On the other hand, if the new teams are in markets of inferior quality to the current collection of teams, than expansion may lead to an overall reduction in average demand. In consideration of the fact that leagues should choose to expand under situations that would most benefit the league, it is expected that new franchises should increase average league attendance.

Franchise Relocations. The decision to relocate a franchise to a new market is usually made under the pretext that its existing market is no longer able to adequately support a professional sports team. If this is true, the relocation should result in greater fan support in the new, better market. At the league level, the number of franchise relocations in a given year is therefore expected to contribute to greater average attendance.

New Stadiums. The construction of a new stadium or the significant renovation of an old stadium is expected to lead to an increased demand to attend games, as fans are curious and excited about a team's glitzy new home. At the league level, the number of new or majorly renovated stadiums that open each year is therefore expected to impact league-wide attendance, with a larger number of new stadiums contributing to greater attendance, all else equal.

Stadium Capacity. In addition to the newness of a stadium, its size could also be a factor affecting ticket demand. Even in the absence of sell-outs, a larger stadium with more ticket inventory may lead to greater sales. Some of this potential increase may be due to lower average ticket prices for the excess capacity, but this effect (if present) would be captured by the ticket price control. Conversely, following the new trend started by the Baltimore Orioles in the early 1990s to build smaller, more fan-friendly stadiums/arenas, stadium capacity might be inversely related to demand for tickets. Weighing these two potential effects of stadium capacity on attendance, it is expected that capacity will positively affect attendance.

Seasonal Competitive Balance. Although this study is not directly concerned with measuring the effect of match or seasonal competitive balance on attendance, the UOH suggests that all forms of competitive balance can affect the demand for professional sports in a given match or a given season. As a result, it is important to control for other forms of competitive balance to avoid spurious findings on the proposed competitive balance measures of interest. Since this study investigates the demand for professional sports at the yearly level, only a seasonal competitive balance control is needed. The most commonly used seasonal competitive balance metric in the literature is the ratio of actual to idealized standard deviation of win percentages, where a larger ratio (corresponding to a lower level of competitive balance) is expected to lead to a decrease in attendance. In this study, this metric is calculated for only the middle third of teams in the final standings in order to get a competitive balance measure that is more relevant for the teams that are competitive for a playoff position. As this measure increases, playoff contending teams are more widely separated in the standings and the excitement of the playoff race may be diminished, leading to lower attendance. So as not to create endogeneity issues with the playoff percent variables of interest but still to retain the essence of the importance of the tightness of the standings regarding playoff contending teams, a common metric of the middle one third of teams is used regardless of where the actual playoff cut line falls in a given season.

Strikes/Lockouts. Significant strikes or lockouts in professional sport leagues that lead to canceled games are expected to negatively affect fan interest during the remaining games of the strike or lockout season. Therefore, dummy variables are included for each league-year that witnessed a strike or lockout that was severe enough to cause regular season games to be canceled. These seasons are 1972 (MLB strike), 1981 (MLB strike), 1994 (MLB strike), 1994-95 (NHL lockout), 1998-99 (NBA lockout), 2004-05 (NHL lockout), 2011-12 (NBA lockout) and 2012-13 (NHL lockout). The 1994 MLB strike and the 2004-05 NHL lockout were so severe that they led to the cancelation of the postseason in addition to regular season games. As a result, these two league years are not included in the data analysis and the dummy variable for each of these work stoppages is attributed to the following year instead.

Attendance Trend. In addition to all of the previous control variables motivated by economic theory, a trend control variable is needed to account for other unexplained factors that have contributed to the general rise in popularity of sports over the past 60 years. For example, one factor that this trend may account for is the rise in the coverage of and interaction with professional sports over time. Innovations such as 24-hour sports networks (e.g. ESPN) as well as fantasy sports have greatly increased the exposure of professional sports and the ability of fans to constantly follow and be involved with the latest sport news. However, factors such as these are difficult to directly model. In order to best model this underlying demand for professional sports, the average attendance in the other professional sport leagues is used as a control for the league in question. For the MLB regression model, the attendance trend variable is the average attendance per game of the NHL and NBA. Likewise, for the NHL and NBA regressions, the attendance trend variable is the average attendance per game of the MLB and NBA, and MLB and NHL, respectively. The choice of this control variable is appropriate considering the underlying demand for a given major professional sports league is likely driven by the same factors that contribute to the underlying demand for other major professional leagues.

4.3 H2 Model Specification

The following regression equation serves as the foundation for the analysis of the second hypothesis:

League-wide Attendance = Consecutive Season Competitive Balance + Playoff Percent + Playoff Percent^2 + Control Variables

This model is a direct extension of the regression equation used in the test of H1 (see section 4.1) with one new independent variable testing the effect of consecutive season competitive balance. As such, the dependent variables and all of the control variables are the same as previously discussed. The final baseline first difference regression model used to test hypothesis 2 is shown below for MLB, the NHL, and the NBA:

MLB: AvgAttendPGFD(y) = CSCBFD(x1) + PlayoffPctFD(x2) + PlayoffPct2FD(x3) + AvgCapacityFD(x4) + RealTicketPriFD(x5) + NewFranchise(x6) + Relocation(x7) + NewStadium(x8) + CenSeasonCBFD(x9) + Strike72(x10) + Strike81(x11) + Strike94(x12) + AttendTrendFD(x13) + error

NHL: AvgAttendPGFD(y) = CSCBFD(x1) + PlayoffPctFD(x2) + PlayoffPct2FD(x3) + AvgCapacityFD(x4) + NewFranchise(x5) + Relocation(x6) + NewStadium(x7) + CenSeasonCBFD(x8) + Lockout94(x9) + Lockout04(x10) + Lockout12(x11) AttendTrendFD(x12) + error

NBA: AvgAttendPGFD(y) = CSCBFD(x1) + PlayoffPctFD(x2) + PlayoffPct2FD(x3) + AvgCapacityFD(x4) + RealTicketPriFD(x5) + NewFranchise(x6) + Relocation(x7) + NewStadium(x8) + CenSeasonCBFD(x9) + Lockout98(x10) + Lockout11(x11) + AttendTrendFD(x12) + error

Where all of the variables are the same as in the previous model (see section 4.1) except for:

CSCBFD is the first difference of the consecutive season competitive balance measure of interest for a given study. Specific variables used in this study are:

1. **POChurnFD** is the first difference of the percentage of playoff qualifying teams in the current league-year that did not qualify for the playoffs the previous season.
2. **POChurnLFD** is the lag of POChurnFD.
3. **POChurn3FD** is the first difference of the average of the playoff churn for the previous three seasons.
4. **POChurnW3FD** is the first difference of the weighted average of the playoff churn for the previous three seasons, with the previous season given a weight of

1.0, the season prior to that given a weight of 0.67, and the season prior to that given a weight of 0.33.

5. **CChurnFD** is the first difference of a dummy variable equaling 1 if the current season saw a new champion and 0 if the current season was a repeat champion from the year prior.
6. **CChurnLFD** is the lag of CChurnFD.
7. **CGChurnFD** is the first difference of the percentage of teams in the championship game in the current league-year that did not reach the championship game in the previous season.
8. **CGChurnLFD** is the lag of CGChurnFD.
9. **SeasChurnFD** is the first difference of the adjusted churn of the final season standings compared with the mid-season standings.
10. **SeasChurnLFD** is the lag of SeasChurnFD.
11. **AvgPOYrsFD** is the first difference of the average number of years since each team in a given league last reached the playoffs divided by the ideal average representing complete turnover in playoff teams every year.
12. **AvgPOYrsLFD** is the lag of AvgPOYrsFD.
13. **LFChurnFD** is the first difference of the percentage of teams in the league (conference) finals in the current league-year that did not reach the league (conference) finals game in the previous season.
14. **LFChurnLFD** is the lag of LFChurnFD.

15. **LSFChurnFD** is the first difference of the percentage of teams in the league (conference) semi-finals in the current league-year that did not reach the league (conference) semi-finals in the previous season.
16. **LSFChurnLFD** is the lag of LSFChurnFD.

Descriptive statistics for the preceding variables can be seen below in Table 4 for MLB, Table 5 for the NHL and Table 6 for the NBA.

Table 4: MLB H2 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
POChurnFD	0	0.387056	-1	1
POChurnLFD	0.001667	0.406068	-1	1
POChurn3FD	0.004167	0.138420	-0.33333	0.375
POChurnW3FD	0.005532	0.167983	-0.33333	0.416667
CChurnFD	0.016129	0.461357	-1	1
CChurnLFD	0.016393	0.465181	-1	1
CGChurnFD	0.011628	0.353358	-0.5	1
CGChurnLFD	0.011905	0.357636	-0.5	1
SeasChurnFD	-0.000655	0.091497	-0.23438	0.208333
SeasChurnLFD	0.001342	0.090849	-0.23438	0.208333
AvgPOYrsFD	0.025359	0.698104	-3.39860	3.370629
AvgPOYrsLFD	0.032212	0.701659	-3.39860	3.370629

Table 5: NHL H2 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
POChurnFD	0.006510	0.143578	-0.375	0.375
POChurnLFD	0.005319	0.144890	-0.375	0.375
POChurn3FD	0.006019	0.057372	-0.09722	0.208333
POChurnW3FD	0.005556	0.069667	-0.13194	0.270833
CChurnFD	0.020833	0.635462	-1	1
CChurnLFD	0.021277	0.642325	-1	1
CGChurnFD	0.020833	0.412031	-1	1
CGChurnLFD	0.021277	0.416474	-1	1
SeasChurnFD	0.001296	0.218985	-0.89349	0.928994
SeasChurnLFD	0.001324	0.221352	-0.89349	0.928994
AvgPOYrsFD	-0.002720	1.086963	-5	1.333333
AvgPOYrsLFD	0.003571	1.097563	-5	1.333333
LFChurnFD	0.005814	0.280775	-0.5	0.75
LFChurnLFD	0.011905	0.281288	-0.5	0.75
LSFChurnFD	0.013889	0.181211	-0.375	0.375
LSFChurnLFD	0.010714	0.182838	-0.375	0.375

Table 6: NBA H2 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
POChurnFD	-0.001462	0.137083	-0.33333	0.375
POChurnLFD	-0.003720	0.137250	-0.33333	0.375
POChurn3FD	0.001157	0.047912	-0.125	0.133333
POChurnW3FD	0.001286	0.057582	-0.11111	0.1375
CChurnFD	-0.017544	0.582213	-1	1
CChurnLFD	0	0.572078	-1	1
CGChurnFD	0	0.534523	-1	1
CGChurnLFD	0	0.539360	-1	1
SeasChurnFD	-0.002047	0.131467	-0.5	0.375
SeasChurnLFD	-0.000337	0.132016	-0.5	0.375
AvgPOYrsFD	-0.041708	1.122849	-4.5	2.92716
AvgPOYrsLFD	-0.041103	1.132821	-4.5	2.92716
LFChurnFD	0	0.258775	-0.5	0.5
LFChurnLFD	0	0.261117	-0.5	0.5
LSFChurnFD	0.003378	0.165324	-0.375	0.5
LSFChurnLFD	0.003472	0.167668	-0.375	0.5

Looking at Tables 4-6, the descriptive statistics for the consecutive season competitive balance measures match expectations. Similar to the discussion of the descriptive statistics in Tables 1-3, the relatively large magnitude of the standard deviation for each variable relative to its mean is due to first differencing. As a result, the mean values are generally expected to be around zero, with both positive and negative changes throughout the data set leading to the relatively high standard deviations. In addition, the statistics are generally consistent across leagues, with all variables having a mean value very close to zero. However, the small positive value for most variables in both MLB and the NHL suggests that the level of consecutive season competitive balance (as measured by these 16 different metrics) has slowly increased over time, while the opposite is true for the NBA. These trends support the conclusion of previous competitive balance studies that show that the NBA has the lowest level of competitive balance among the major leagues in the United States.

4.4 H2 Research Variables

The dependent variable and all of the control variables are the same in the H2 regression model as previously described for H1 (see section 4.2). The only difference involves the independent variables of interest, which now include a variety of novel consecutive season competitive measures described below.

Consecutive Season Competitive Balance. The proposed consecutive season competitive balance measures are the independent variables of interest in the test of H2. Most of these new competitive balance measures consist of a calculation of the percent of teams in a given round of the playoffs in the current year that is different from the year prior. This calculation is called the churn, and for the NBA and NHL, the churn is calculated on five different levels: playoff qualification, advancing to the league (conference) semi-finals, advancing to the league (conference) finals, advancing to the championship game, winning the championship. For example, in the 2011-2012 season for the NBA, the following sixteen teams qualified for the playoffs: Boston Celtics, Indiana Pacers, Miami Heat, Philadelphia 76ers, Los Angeles Clippers, Los Angeles Lakers, Oklahoma City Thunder, San Antonio Spurs, Atlanta Hawks, Orlando Magic, New York Knicks, Chicago Bulls, Memphis Grizzlies, Denver Nuggets, Dallas Mavericks, and Utah Jazz. Of those teams, only the Los Angeles Clippers and Utah Jazz did not qualify for the playoffs the year before (taking the place of the Portland Trailblazers and the New Orleans Hornets that did), and thus the playoff qualification competitive balance measure would be 2/16 = 0.125.

The first eight teams in the previous list advanced to the second round of the playoffs in 2011-12, and four of those did not do so the year before: Pacers, 76ers, Clippers, Spurs. Therefore, the second round competitive balance measure would be 4/8 = 0.5. Of the four teams that made the league championship games in 2011-12, two were different from the previous year (Celtics, Spurs), so the league championship round competitive balance measure would be 2/4 = 0.5. The same 0.5 calculation is true for the championship game measure, where one of the two teams (Thunder) was different compared to the year before. Lastly, the championship winning measure would be 1, as the Miami Heat won the championship and did not do so the year before.

Although the previous example calculated these five inter-seasonal competitive balance metrics using only the difference with the prior year's playoff results, two additional specifications for the playoff qualification churn average the results (using either a simple or a weighted average) over a three year time period. The simple average assumes that fans are equally sensitive to playoff qualification in each of the past three seasons in terms of their taste for consecutive season competitive balance. The three year weighted average assigns weights of 1.0 for the playoff qualification churn computed for the prior year, 0.67 for two years prior, and 0.33 for three years prior. This specification assumes fans are most sensitive to more recent results. In all cases, the level of churn is expected to affect attendance with higher churn (greater competitive balance) leading to higher attendance.

In addition to the playoff churn variables, two other consecutive season competitive balance measures were included in this study: the adjusted seasonal churn of the standings from mid-season to the end of the season, and the average number of years since each team last made the playoffs. For the adjusted seasonal churn, it is expected that greater churn in the standings as the season progresses will lead to higher attendance. For the average number of years variable, it is expected that reducing the average will lead to higher attendance. For all of the consecutive season competitive balance measures used to test H2, the variables are calculated for the current year and then also included as a lag variable from the previous year. This is done because the result of several of these variables would be uncertain or incomplete to fans during the current regular season and therefore the lag variables would likely be a better measure of the fans' perception of the level of consecutive season competitive balance.

CHAPTER 5

RESULTS AND DISCUSSION

The variables and methods defined in Chapter 4 were used to perform the empirical analysis to test the stated hypotheses. The presentation and discussion of the results follows in three sections: results concerning the first hypothesis, results concerning the second hypothesis, and results concerning the control variables. The last two sections of this chapter discuss alternate models that highlight the robustness of the results followed by a broad discussion of the totality of the results.

5.1 Playoff Structure UOH Hypothesis

The H1 regression models from the previous chapter were estimated in Stata using the two step approach, starting with the control variables and adding in the independent variables to determine an increase in explanatory power. Support for the hypotheses was gauged through the significance of the respective parameter estimates. Table 7 below display the results of the regressions testing H1. For MLB and the NHL, inclusion of the playoff structure independent variables (Model 2) increases the significance of the model when compared to the baseline model (Model 1) of only control variables. For MLB, the adjusted R-squared is 0.42 for the baseline model and 0.59 when the playoff structure variables are included. For the NHL, the adjusted R-squared is 0.36 for the baseline model and 0.42 when the playoff structure variables are included. For both leagues, the playoff variables are statistically significant at the 5% level or better, giving support to the underlying notion of hypothesis 1 that the percentage of teams that qualify for the playoffs is an important driver of fan interest.

For the NBA, the adjusted R-squared drops when the playoff structure variable is included, but this model suffers from complete multicollinearity with the independent variables and some of the control variables. Because of this, Model 2 does not contain the square term of playoff percent and the resulting parameter estimates are considered less reliable. Further tests looking at a limited subset of variables give results that are relatively consistent with those of MLB and NHL, giving confidence that the NBA exhibits underlying trends that are consistent with the other leagues. However, due to the desire to maintain a common baseline regression model across all of the studied leagues, the NBA data unfortunately does not allow a complete analysis of the effect of the desired independent variables. For this reason, the following discussion of the playoff percent variables will focus on MLB and the NHL. Discussion of the results for the controls variables as well as the independent variables of interest for hypothesis 2 includes all three leagues.

Table 7: H1 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent	MLB		NHL		NBA	
Variable	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
PlayoffPctFD		-154082 (0.001)*		-60447.9 (0.019)*		-32554.6 (0.855)
PlayoffPct2FD		298958.1 (0.002)*		49518.87 (0.019)*		
AvgCapacityFD	0.199706 (0.454)	-0.30569 (0.245)	0.308347 (0.440)	0.374380 (0.328)	0.107210 (0.303)	0.103778 (0.348)
RealTicketPriFD	-228.984 (0.358)	-14.1976 (0.948)	-16.4925 (0.346)	-19.0298 (0.226)	23.15256 (0.362)	21.62952 (0.438)
NewFranchise	567.6262 (0.036)*	1133.058 (0.000)*	-316.605 (0.000)*	-332.230 (0.000)*	188.8466 (0.160)	-454.583 (0.897)
Relocation	-691.968 (0.443)	569.8633 (0.491)	-158.428 (0.443)	-138.758 (0.482)	-28.4393 (0.855)	-34.9552 (0.834)
NewStadium	267.8742 (0.333)	0.622449 (0.998)	152.1006 (0.137)	128.8015 (0.188)	38.34482 (0.390)	38.86651 (0.407)
CenSeasonCBFD	-1596.55 (0.149)	-1876.32 (0.059)	-12.3368 (0.954)	-23.8569 (0.907)	-578.015 (0.008)*	-587.152 (0.012)*
Strike72	218.8468 (0.891)	-1105.49 (0.430)				
Strike81	-2068.32 (0.112)	1493.813 (0.332)				
Strike94	-6776.54 (0.000)*	-3229.08 (0.029)*				
Lockout94			-73.7150 (0.894)	-72.6770 (0.890)		
Lockout04			-164.276 (0.775)	-172.056 (0.754)		
Lockout12			8.095109 (0.988)	-0.64434 (0.999)		
Lockout98					-1482.43 (0.005)*	-1490.74 (0.008)*
Lockout11					-216.945 (0.378)	-223.605 (0.392)
AttendTrendFD	0.041715 (0.929)	0.522442 (0.221)	0.248586 (0.035)*	0.245086 (0.030)*	0.086633 (0.148)	0.096560 (0.248)
Adj. R-Squared	0.4206	0.5910	0.3631	0.4207	0.4498	0.3970

P-values in parentheses
*significant at the 5% level or better

For both MLB and the NHL, the statistically significant parameter estimates on the playoff percent variables allow for the effect of changes to their respective playoff structures to be interpreted. Because of the playoff percent squared term, this interpretation of the results requires a base level percent of teams that qualify for the playoffs. For MLB, the current percentage of playoff qualifying teams (10/30 = 33%) can be used as this base level in order to evaluate the effect of potential future changes to the playoff structure. The first important conclusion from this analysis is that the current percentage of playoff qualifying teams in MLB falls on the upward sloping region of the quadratic, suggesting that further increasing the number of teams that qualify for the playoffs will yield a positive attendance response. In fact, if two more teams were added to the MLB playoffs (12/30 = 40%), it is calculated that average per game attendance would be expected to rise by over 4,000 (see Table 8). This is a very sizable increase (over 10% of the current per game attendance average for MLB), but care must be taken because this calculation represents an extrapolation outside of the bounds of the MLB data set where the playoff percent variable ranges from 10%-33%. Nevertheless, these results provide evidence that further increasing the number of teams that qualify for the MLB playoffs should have a positive effect on regular season attendance.

Table 8: MLB Playoff Structure Results for Select Years

Year	Change in Playoff Teams	Change in Playoff Percent	Change in Average Attendance per Game
1969	2 (from 2 to 4)	6.7% (from 10% to 16.7%)	-4,957
1995	4 (from 4 to 8)	14.3% (from 14.3% to 28.6%)	-3,708
2012	2 (from 8 to 10)	6.7% (from 26.7% to 33.3%)	1,686
Current	2 (from 10 to 12)	6.7% (from 33.3% to 40.0%)	4,343 (projected)

From a historical perspective, the analysis is less clear cut due to the quadratic nature of the attendance response. In 1950, the first year of the data set, only two out of the 16 teams qualified for the playoffs. These two teams were their respective league champions (pennant winners) and played each other in the World Series. This system of regular season league champions meeting directly in the World Series existed in MLB from 1903 to 1968. During this time, there were no inter-league games between the National and American Leagues, so the World Series was a distinctly separate and unique event from the regular season. In this way, the regular season was of utmost importance and was not diluted at all by a playoff system. In each of the two leagues the teams played against each other throughout the season in order to win the pennant and every game mattered in the final standings. This reliance on the regular season as the only season is historically important in MLB and likely is the underlying reason why increasing the number of teams that qualified for the playoffs in 1969 and 1995 led to a reduction in average attendance.

Looking at Table 8, it can be seen that moving from the playoff structure that existed in 1968 to that in 1969 (when four teams first made the playoffs) was met with a decrease in average attendance per game of almost 5,000. This was followed by another reduction of almost 4,000 when the number of playoff teams was doubled to eight in 1995. Although the expectation is that increasing the percentage of teams that qualify for the playoffs will increase fan excitement due to the greater number of teams that are competitive for a playoff spot, this consideration was not enough to overcome the erosion of the importance of the regular season. Baseball traditionalists to this day still speak negatively of the expansion of the playoffs, especially the 1995 expansion that introduced the wild-card spots. Because of this strong value that MLB fans place on the historical significance of the regular season and the pennant race, the early era of just two teams qualifying for the World Series is the playoff structure that is expected to lead to the greatest regular season fan response within the 1950-2013 data set.

Although the dilution of the importance of the regular season drove a negative fan response through playoff expansion up to eight teams, the positive quadratic nature of this response suggests that further expansion would lead to higher attendance. This is likely due to the fact that at higher levels of playoff qualifying teams, the gains from the increase in the number of teams that are competitive for a playoff spot start to outweigh the losses from the reduction in the importance of the regular season. This change can be attributed to two underlying factors. First, a change from two to four playoff teams, for example, will likely incorporate fewer new competitive teams than a change from eight to ten or ten to twelve. This is due to the fact that the distribution of the finals standings most often resembles a bell curve with the largest concentration of teams near the middle. Therefore, the closer the playoff cut line gets to the middle, the larger the number of new teams that will now be competitive for a playoff spot. Second, the expansion of the MLB playoffs thus far has already initiated the process of reducing the importance of the regular season and has therefore taken most of the bite out of further expansion. Due to these reasons, the expansion of the playoffs in 2012 (going from eight teams to 10) was estimated to increase the per-game average attendance by around 1,700. This is an increase of about 5% of the current average attendance and thus represents a meaningful increase in fan interest and corresponding league-wide profits. Based on this analysis, it appears wise that MLB increased the number of playoff qualifying teams in 2012.

In consideration of these complete findings, however, it can be questioned whether MLB should ever have expanded at all, or whether it should in fact go back to the pre-1969 days of only the two pennant winners making the World Series. Looking again at Table 8, the net effect of the large-scale changes to the playoff structure that MLB has implemented over time has been negative. One can thus hypothesize that MLB may have been better off never changing its playoff structure. However, two considerations suggest that playoff expansion in MLB as a whole could be advantageous overall. First, this study does not consider the attendance or profitability of the playoffs due to the reasons discussed in Chapter 4. However, it is expected that increasing the number of playoff games (due to adding more teams and more rounds into the playoffs), would lead to an increase in postseason attendance and revenue. As a result, even though playoff expansion may have negatively affected regular season attendance in 1969 and 1995, it's possible (though unlikely) that additional playoff revenue would have been enough to overcome those losses.

The second consideration relates directly to the results of this analysis, which suggest that even further playoff expansion would occur along the upward sloping region of the quadratic response, leading to important regular season attendance gains. Although the attendance response to playoff structure is based solely on the bounds within the data set (playoff percentages from 10-33%), it is reasonable to expect the trend to continue for regions near the bounds. If this is true, further expansion of the MLB playoffs to 12 teams (12/30 = 40%), would lead to a gain in regular season attendance that would largely offset the overall losses due to expansion from 1950 to 2013. In addition, such an increase in average attendance would be more impactful than the decreases in attendance observed in 1969 and 1995 because there are currently more teams in MLB (30 currently compared to 28 in 1995 and 24 in 1969). With more teams, a given change in average attendance imparts a larger change in total aggregate attendance.

For the NHL, the analysis of the results follows a similar, but somewhat opposite argument. In this case, the current percentage of playoff qualifying teams (16/30 = 53%) falls on the downward sloping region of the quadratic, suggesting that decreasing the number of teams that qualify for the playoffs will yield a positive attendance response (see Table 9 below). In fact, if two teams were removed from the NHL playoffs (14/30 = 47%), it is calculated that average per game attendance should rise by over 700. This is a sizable increase (about 4% of the current per game attendance average for the NHL), but again care must be taken because this calculation represents an extrapolation outside of the bounds of the NHL data set where the playoff percent variable ranges from 50%-76%. Nevertheless, these results suggest that decreasing the number of teams that qualify for the NHL playoffs should have a positive effect on regular season attendance.

Table 9: NHL Playoff Structure Results for Select Years

Year	Change in Playoff Teams	Change in Playoff Percent	Change in Average Attendance per Game
1974	4 (from 8 to 12)	16.7% (from 50% to 66.7%)	-446
1979	4 (from 12 to 16)	5.6% (from 70.6% to 76.2%)	685
2000	0 (from 16 to 16)	-22.9% (from 76.2% to 53.3%)*	-844*
Current	-2 (from 16 to 14)	-6.7% (from 53.3% to 46.7%)	729 (projected)

*cumulative effect from 1991 to 2000 due to franchise expansion from 21 to 30 teams

Conversely, if the NHL were to increase the number of teams that make the playoffs there would be an expected negative effect on attendance. If two teams were added to the NHL playoffs (increasing the playoff percentage to 60%), it is calculated that the per-game average attendance would drop by almost 300. This is a decrease of about 1.5% of the current average attendance which is a small, but important reduction in fan interest and corresponding league-wide profits. However, this does not tell the whole story due to the quadratic nature of the attendance response to playoff structure.

Although small increases to the current playoff percent are expected to decrease attendance, the historical high attendance point for the league (in regards to the playoff structure), occurred in 1979 following the increase in the number of playoff qualifying teams to 16 (76% of the 21 teams). As a result, the slow dilution of the percentage of playoff qualifying teams from 76% in 1979 to 53% today through franchise expansion actually led to a cumulative decrease in average attendance of about 800. This is just one small piece of the complicated history of playoff structural changes in the NHL and the corresponding attendance response.

In the era of the Original Six, which lasted through 1966, there were six teams in the NHL and four of them made the playoffs each year (66.7%). Through franchise expansion in the late 1960s and early 1970s (even after increasing the number of playoff teams from four to eight in 1967), the playoff percentage declined to the historic low in the NHL of 50% in 1973. However, in the following year the number of playoff teams was increased from eight to 12 which brought the playoff percentage back to the Original Six levels and was expected to reduce per game attendance by over 400. In 1979, the bump in playoff teams from 12 to 16 brought the playoff percent to its historic high of 76% and with it an increase in attendance per game of around 700.

Although this history of changes in the NHL is more difficult to follow than the simpler linear history of the MLB, the same general pattern emerges during the years within the data set. However, unlike MLB, the historical NHL standard of 66.7% of teams qualifying for the playoffs is essentially the least preferred outcome, with changes in either direction being met with a positive response. So while tradition is the bellwether of fan interest in MLB, novelty seems to rule the day in the NHL. This fundamental difference between the fans of MLB and the NHL makes sense when one considers the immense differences in the history of the two leagues. Major League Baseball is the oldest professional league in the United States and had already been well established for decades with 16 consistent teams before the NHL was even founded. By the time of the first MLB playoff expansion in 1969, 20 of the current 30 MLB teams were already in existence. Therefore, a majority of the current MLB teams (and their fans) knew and appreciated the game under its original World Series only regime. In the NHL, on the other hand, only six teams existed before the first playoff expansion in 1967. Although these six teams are rooted in history and are arguably the six most fan supported teams, they now represent only one fifth of the current league members. The vast majority of NHL teams in the United States (and their fans) therefore don’t have a tradition rich history and are likely more prone to be fair weather fans that lose interest in attending games if their favorite teams are playing badly. These preferences likely dominate the league level analysis.

In consideration of this observation, the results suggest that large increases or decreases in the percentage of playoff qualifying teams would be met with a positive attendance response. However, this result should not be extrapolated too far outside of the bounds of the data set, as increasing the playoff percent to 100%, for example, would certainly lead to a significant negative effect on the regular season as it would be essentially meaningless. Therefore, any proposed changes to the playoff structure in the NHL or MLB should err on the side of taking advantage of the path of least resistance. In the NHL, this means a reduction in the percentage of teams qualifying for the playoffs while for MLB, it is means the opposite.

Although the fan responses to playoff structure in MLB and the NHL were shown to be fundamentally different due to the historical underpinnings of the leagues, the results do raise an important question of whether there is a percent of playoff qualifying teams that would maximize attendance in one or both leagues. Although there is no data in either league for playoff percentages between 33% and 50%, it is conceivable to think that regular season attendance (and fan interest) may be maximized for some percentage of playoff qualifying teams that falls within this range. Such an idea is consistent with the thought that at lower levels of playoff qualification (less than 33%), adding playoff teams furthers the excitement of the playoff race and increases the number of teams that are competitive for a playoff spot while still preserving the importance of the regular season. However, at high levels of playoff qualification (greater than 50%), this positive effect of adding playoff teams is not sufficient to overcome the negative effects of shifting the importance of a season from the regular season to the playoffs. Although the results do not lend direct support to this theory, they do provide evidence in favor of increasing the number of teams that make the playoffs in MLB and decreasing the number in the NHL. Furthermore, as a whole, the regression results provide significant support of hypothesis 1 that playoff structure is an important driver of fan interest.

5.2 Consecutive Season UOH Hypothesis

The H2 regression models from the previous chapter were estimated in Stata for each of the 16 consecutive season competitive balance measures in this study. Support for the hypotheses was gauged through the significance of the respective parameter estimates.

The regression results in Table 10 (MLB), Table 11 (NHL), and Table 12 (NBA) show the analysis for the second hypothesis concerning the effect of consecutive season competitive balance on attendance. Models 1 through 16 each add one consecutive season competitive balance measure to the regression to observe if there is an increase in the explanatory power of the model compared with the H1 regression model. The first four new measures (Models 1-4) explore the effect of the churn of playoff qualifying teams, including looking at the current season, the previous season, and an average of the last three seasons. Models 5-8 (and 13-16 for the NHL and the NBA) investigate the effect of the churn of playoff advancing teams. Models 9 and 10 look at the churn in the standings from mid-season to the end of the season while Models 11 and 12 look at the average number of years since each team in the league last qualified for the playoffs. For MLB and the NBA, none of the proposed inter-season competitive balance measures increase the adjusted R-squared and none of them are statistically significant. For the NHL, only one of the variables increases the adjusted R-squared (from 0.42 to 0.48) and is statistically significant at the 5% level. In consideration of the fact that 44 different tests were completed across the three different leagues (12 for MLB, 16 each for the NHL and the NBA), and only one instance of a consecutive season competitive balance measure was found to be statistically significant, it is very likely that this is due to chance. With significance testing at the 5% level, there is a one in 20 chance of making a type I error so across 44 tests this is a strong possibility. In light of these results, there is no or very minimal support that the level of consecutive season balance (at least as conceptualized by this expansive set of independent variables) has any significant effect on attendance.

Table 10: MLB H2 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-161692	-151416	-162173	-156479	-152847	-148617	-103467	-90959.7
	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.001)*	(0.117)	(0.173)
PlayoffPct2FD	314688.5	292831.5	312853.4	303809	296262.2	287623.8	193301.5	164772.7
	(0.001)*	(0.002)*	(0.002)*	(0.002)*	(0.002)*	(0.003)*	(0.153)	(0.228)
POChurnFD	542.6759							
	(0.346)							
POChurnLFD		253.2317						
		(0.609)						
POChurn3FD			-1115.70					
			(0.525)					
POChurnW3FD				-472.780				
				(0.733)				
CChurnFD					-128.999			
					(0.713)			
CChurnLFD						-277.509		
						(0.440)		
CGChurnFD							402.5349	
							(0.434)	
CGChurnLFD								-781.468
								(0.129)
AvgCapacityFD	-0.30915	-0.27542	-0.35128	-0.32280	-0.29016	-0.28836	-0.63355	-0.75725
	(0.241)	(0.311)	(0.203)	(0.235)	(0.282)	(0.277)	(0.058)	(0.053)
RealTicketPriFD	37.65616	-21.1086	10.65869	-0.67813	-21.7673	1.463745	-167.736	-150.732
	(0.868)	(0.924)	(0.962)	(0.998)	(0.922)	(0.995)	(0.494)	(0.528)
NewFranchise	1114.129	1155.426	1101.496	1113.294	1126.205	1066.731	1378.331	1330.792
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.001)*	(0.000)*	(0.001)*
Relocation	972.9403	363.5496	953.0447	742.2449	559.2683	591.3492	-776.565	-763.685
	(0.299)	(0.695)	(0.357)	(0.449)	(0.506)	(0.478)	(0.494)	(0.478)
NewStadium	-27.1419	31.56578	-46.9765	-24.3172	10.91262	-38.7273	-173.667	-325.085
	(0.914)	(0.903)	(0.857)	(0.926)	(0.966)	(0.879)	(0.550)	(0.274)
CenSeasonCBFD	-1689.82	-1886.85	-1698.98	-1806.77	-1792.46	-1739.76	-1687.46	-1450.99
	(0.095)	(0.061)	(0.102)	(0.079)	(0.082)	(0.086)	(0.111)	(0.162)
Strike72	-1516.17	-868.983	-1572.73	-1357.94	-1112.71	-1189.37		
	(0.304)	(0.559)	(0.325)	(0.397)	(0.433)	(0.401)		
Strike81	1835.571	1476.409	2133.095	1691.009	1477.639	1372.377	1200.655	1425.014
	(0.249)	(0.344)	(0.252)	(0.311)	(0.344)	(0.378)	(0.467)	(0.412)
Strike94	-3313.49	-3159.49	-3161.59	-3324.82	-3232.47	-3015.94	-4014.43	-3695.71
	(0.026)*	(0.035)*	(0.034)*	(0.029)*	(0.031)*	(0.045)*	(0.033)*	(0.043)*
AttendTrendFD	0.510242	0.498610	0.606125	0.560720	0.527011	0.497963	-0.14668	-0.08680
	(0.233)	(0.251)	(0.180)	(0.211)	(0.224)	(0.248)	(0.856)	(0.915)
Adj. R-Squared	0.5900	0.5817	0.5836	0.5798	0.5800	0.5861	0.6276	0.6565

P-values in parentheses
*significant at the 5% level or better

Table 10, continued: MLB H2 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 9	Model 10	Model 11	Model 12
PlayoffPctFD	-151694 (0.001)*	-153847 (0.001)*	-154955 (0.002)*	-160423 (0.001)*
PlayoffPct2FD	293417.6 (0.002)*	296443.2 (0.002)*	299548.6 (0.002)*	306397.7 (0.002)*
SeasChurnFD	1266.988 (0.505)			
SeasChurnLFD		-2076.95 (0.253)		
AvgPOYrsFD			32.47094 (0.956)	
AvgPOYrsLFD				-166.767 (0.500)
AvgCapacityFD	-0.29707 (0.263)	-0.31736 (0.226)	-0.30423 (0.257)	-0.35151 (0.201)
RealTicketPriFD	-0.49917 (0.998)	-58.0458 (0.793)	-14.5990 (0.948)	-50.4980 (0.824)
NewFranchise	1106.029 (0.000)*	1133.199 (0.000)*	1135.709 (0.000)*	1169.759 (0.00)*
Relocation	606.9521 (0.469)	505.0319 (0.541)	569.6125 (0.498)	634.4742 (0.451)
NewStadium	-63.3031 (0.813)	-21.6803 (0.930)	-1.18315 (0.996)	28.83612 (0.909)
CenSeasonCBFD	-1786.42 (0.077)	-1609.96 (0.111)	-1879.81 (0.063)	-1881.06 (0.061)
Strike72	-1164.19 (0.411)	-1173.91 (0.401)	-1112.58 (0.436)	-1290.75 (0.371)
Strike81	1451.775 (0.351)	1602.559 (0.298)	1473.305 (0.360)	2085.523 (0.245)
Strike94	-3415.58 (0.025)*	-3154.12 (0.032)*	-3191.68 (0.052)	-2798.90 (0.081)
AttendTrendFD	0.559432 (0.199)	0.554644 (0.194)	0.524964 (0.229)	0.583050 (0.186)
Adj. R-Squared	0.5841	0.5954	0.5783	0.5843

P-values in parentheses
*significant at the 5% level or better

Table 11: NHL H2 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-60632.8 (0.024)*	-54702.5 (0.040)*	-57722.2 (0.033)*	-54752.4 (0.044)*	-62653.4 (0.022)*	-59859.7 (0.026)*	-62663.2 (0.022)*	-59331.4 (0.029)*
PlayoffPct2FD	49610.36 (0.024)*	45026.42 (0.039)*	47255.79 (0.033)*	45355.93 (0.041)*	51183.89 (0.022)*	49059.62 (0.026)*	51187.46 (0.022)*	48596.28 (0.028)*
POChurnFD	268.6824 (0.648)							
POChurnLFD		-705.292 (0.251)						
POChurn3FD			-1732.48 (0.260)					
POChurnW3FD				-1701.01 (0.226)				
CChurnFD					-59.2052 (0.656)			
CChurnLFD						38.81881 (0.780)		
CGChurnFD							-100.118 (0.633)	
CGChurnLFD								126.0162 (0.525)
AvgCapacityFD	0.412300 (0.308)	0.456773 (0.251)	0.378004 (0.353)	0.441406 (0.283)	0.370074 (0.353)	0.359953 (0.370)	0.347448 (0.389)	0.380574 (0.343)
NewFranchise	-338.434 (0.000)*	-311.518 (0.000)*	-313.967 (0.000)*	-307.805 (0.000)*	-329.910 (0.000)*	-334.598 (0.000)*	-331.310 (0.000)*	-330.486 (0.000)*
Relocation	-145.753 (0.480)	-227.188 (0.297)	-187.305 (0.383)	-251.748 (0.278)	-156.977 (0.457)	-154.699 (0.480)	-136.095 (0.506)	-144.856 (0.486)
NewStadium	129.1669 (0.204)	159.8464 (0.122)	157.6378 (0.135)	171.3731 (0.112)	134.3204 (0.189)	135.6935 (0.186)	126.3933 (0.214)	123.8516 (0.233)
CenSeasonCBFD	-33.7775 (0.875)	-11.5220 (0.957)	30.3371 (0.894)	46.38737 (0.839)	-49.2818 (0.820)	-12.5189 (0.955)	-64.721 (0.771)	-18.6111 (0.933)
Lockout94	-60.7715 (0.911)	-145.329 (0.788)	-66.9916 (0.903)	-74.1384 (0.893)	-78.3619 (0.886)	-68.1595 (0.901)	-71.4564 (0.896)	-57.6217 (0.917)
Lockout04	-195.007 (0.733)	-259.054 (0.646)	-37.1766 (0.949)	-141.640 (0.805)	-184.855 (0.746)	-172.723 (0.761)	-181.496 (0.750)	-150.534 (0.794)
Lockout12	-15.3239 (0.978)	65.54659 (0.904)	4.436535 (0.994)	6.297602 (0.991)	-4.19851 (0.994)	7.335481 (0.989)	-9.56949 (0.986)	12.31998 (0.982)
AttendTrendFD	0.249723 (0.033)*	0.256316 (0.027)*	0.230277 (0.054)*	0.241124 (0.042)*	0.251334 (0.033)*	0.252747 (0.032)*	0.244492 (0.037)*	0.238280 (0.047)*
Adj. R-Squared	0.3899	0.4219	0.4045	0.4081	0.3898	0.4008	0.3903	0.3892

P-values in parentheses
*significant at the 5% level or better

Table 11, continued: NHL H2 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-61600.8 (0.023)*	-59083 (0.024)*	-58935.5 (0.016)*	-57799.1 (0.027)*	-45656 (0.058)	-44288.1 (0.057)	-55590.1 (0.295)	-35528.7 (0.454)
PlayoffPct2FD	50511.28 (0.023)*	48567.64 (0.023)*	47585.33 (0.018)*	47234.31 (0.028)*	37777.15 (0.055)	36537.01 (0.055)	43577.51 (0.257)	29361.5 (0.392)
SeasChurnFD	-122.372 (0.811)							
SeasChurnLFD		537.3673 (0.169)						
AvgPOYrsFD			195.0162 (0.026)*					
AvgPOYrsLFD				-103.449 (0.171)				
LFChurnFD					-150.385 (0.618)			
LFChurnLFD						258.6376 (0.334)		
LSFChurnFD							307.6289 (0.408)	
LSFChurnLFD								-398.540 (0.267)
AvgCapacityFD	0.366256 (0.354)	0.370683 (0.339)	0.171732 (0.644)	0.268164 (0.497)	0.230099 (0.525)	0.197550 (0.575)	0.312037 (0.389)	0.351288 (0.298)
NewFranchise	-333.476 (0.000)*	-323.030 (0.000)*	-248.045 (0.002)*	-359.425 (0.000)*	-87.9718 (0.367)	-97.6891 (0.289)	-63.6792 (0.587)	-31.5751 (0.771)
Relocation	-140.752 (0.488)	-172.839 (0.393)	-182.078 (0.334)	-87.2958 (0.666)	-81.1602 (0.663)	-33.0363 (0.855)	-29.3158 (0.842)	287.1039 (0.140)
NewStadium	126.4634 (0.211)	167.0717 (0.107)	140.9212 (0.131)	118.3059 (0.234)	105.8268 (0.241)	108.1385 (0.218)	59.14256 (0.455)	-38.2545 (0.651)
CenSeasonCBFD	-26.2798 (0.901)	-8.05260 (0.970)	111.5014 (0.582)	-69.5233 (0.742)	117.2381 (0.616)	92.40101 (0.683)	-181.790 (0.398)	-195.719 (0.325)
Lockout94	42.31354 (0.953)	-92.9728 (0.861)	2.338458 (0.996)	-49.6032 (0.926)	120.2318 (0.802)	212.497 (0.654)	183.3881 (0.638)	222.5797 (0.524)
Lockout04	-191.174 (0.737)	-239.071 (0.668)	-139.969 (0.787)	-187.771 (0.735)	112.583 (0.825)	136.0773 (0.783)	56.91663 (0.886)	-46.9472 (0.898)
Lockout12			107.9263 (0.831)	-29.5586 (0.956)	124.398 (0.799)	119.28 (0.800)	67.51905 (0.858)	178.4943 (0.613)
AttendTrendFD	0.255777 (0.040)*	0.308666 (0.0130*	0.291841 (0.008)*	0.255149 (0.026)*	0.160399 (0.138)	0.159183 (0.125)	0.142410 (0.118)	0.161662 (0.056)
Adj. R-Squared	0.4014	0.4305	0.4808	0.4186	0.0306	0.0608	0.0885	0.2161

P-values in parentheses
*significant at the 5% level or better

Table 12: NBA H2 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-57529.9 (0.767)	-32382.8 (0.894)	-119015 (0.600)	-90108.7 (0.690)	-1401.79 (0.995)	-19471.8 (0.917)	-16272.5 (0.943)	-4624.26 (0.981)
POChurnFD	-368.869 (0.649)							
POChurnLFD		-1.03933 (0.999)						
POChurn3FD			2083.246 (0.514)					
POChurnW3FD				982.4218 (0.653)				
CChurnFD					43.87661 (0.711)			
CChurnLFD						-55.9679 (0.614)		
CGChurnFD							24.3892 (0.900)	
CGChurnLFD								-103.311 (0.602)
AvgCapacityFD	0.105178 (0.363)	0.103825 (0.404)	0.107494 (0.348)	0.092341 (0.433)	0.105064 (0.366)	0.071527 (0.583)	0.109867 (0.386)	0.069779 (0.594)
RealTicketPriFD	18.41723 (0.537)	21.62446 (0.468)	12.67488 (0.688)	19.96131 (0.496)	29.41019 (0.418)	22.97123 (0.432)	22.97097 (0.464)	20.10376 (0.490)
NewFranchise	-953.710 (0.804)	-451.147 (0.926)	-2195.35 (0.626)	-1611.33 (0.720)	133.8181 (0.973)	-201.026 (0.957)	-135.720 (0.976)	114.7863 (0.976)
Relocation	-76.1458 (0.699)	-34.8935 (0.851)	-48.0510 (0.782)	-59.6900 (0.745)	-32.8694 (0.851)	-47.9473 (0.786)	-29.6565 (0.870)	-58.5653 (0.745)
NewStadium	34.48079 (0.488)	38.90329 (0.515)	34.34264 (0.481)	28.30399 (0.600)	29.25952 (0.596)	37.70618 (0.441)	38.53562 (0.437)	47.84314 (0.359)
CenSeasonCBFD	-609.28 (0.016)*	-587.093 (0.021)*	-581.542 (0.017)*	-600.714 (0.016)*	-588.685 (0.017)*	-551.035 (0.028)*	-582.266 (0.020)*	-553.476 (0.027)*
Lockout98	-1500.47 (0.011)*	-1490.51 (0.017)*	-1470.60 (0.011)*	-1547.34 (0.011)*	-1608.29 (0.019)*	-1456.71 (0.013)*	-1516.00 (0.016)*	-1480.03 (0.011)*
Lockout11	-322.436 (0.360)	-223.444 (0.474)	-288.324 (0.320)	-296.878 (0.355)	-232.811 (0.398)	-164.938 (0.574)	-207.909 (0.492)	-160.091 (0.588)
AttendTrendFD	0.108546 (0.238)	0.096532 (0.294)	0.098024 (0.257)	0.102613 (0.248)	0.082886 (0.380)	0.096960 (0.266)	0.092493 (0.324)	0.104409 (0.240)
Adj. R-Squared	0.3461	0.3300	0.3627	0.3457	0.3406	0.3496	0.3312	0.3510

P-values in parentheses
*significant at the 5% level or better

Table 12, continued: NBA H2 Final Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-24067.1 (0.889)	-94847.1 (0.626)	-34778.5 (0.853)	-23069.3 (0.915)	-4193.90 (0.982)	3603.756 (0.983)	-33318.3 (0.859)	115339.6 (0.563)
SeasChurnFD	-1163.11 (0.216)							
SeasChurnLFD		1317.863 (0.146)						
AvgPOYrsFD			36.40834 (0.806)					
AvgPOYrsLFD				10.63017 (0.928)				
LFChurnFD					147.6272 (0.553)			
LFChurnLFD						-258.830 (0.204)		
LSFChurnFD							-62.9269 (0.871)	
LSFChurnLFD								-802.800 (0.175)
AvgCapacityFD	0.104359 (0.331)	0.009687 (0.947)	0.096731 (0.419)	0.105110 (0.373)	0.107490 (0.350)	0.097306 (0.361)	0.101619 (0.387)	0.171288 (0.153)
RealTicketPriFD	27.8653 (0.316)	23.36738 (0.436)	21.45655 (0.465)	23.02894 (0.490)	27.20171 (0.374)	28.41198 (0.305)	21.09246 (0.476)	67.15869 (0.127)
NewFranchise	-275.202 (0.935)	-1710.07 (0.656)	-468.002 (0.899)	-268.735 (0.950)	101.9048 (0.978)	261.8351 (0.939)	-464.194 (0.900)	2494.395 (0.529)
Relocation	-7.37132 (0.964)	-73.9039 (0.670)	-39.3935 (0.824)	-24.7434 (0.906)	23.11059 (0.907)	60.18175 (0.733)	-49.7535 (0.802)	258.607 (0.332)
NewStadium	47.16701 (0.309)	93.25714 (0.322)	35.00431 (0.498)	38.86115 (0.433)	50.2936 (0.340)	47.39875 (0.305)	35.77991 (0.499)	37.16122 (0.405)
CenSeasonCBFD	-659.460 (0.008)*	-580.531 (0.018)*	-587.542 (0.017)*	-582.619 (0.021)*	-573.953 (0.018)*	-556.589 (0.015)*	-572.618 (0.029)*	-904.152 (0.011)*
Lockout98	-1481.53 (0.012)*	-1406.26 (0.013)*	-1473.20 (0.013)*	-1496.48 (0.012)*	-1518.58 (0.010)*	-1460.58 (0.008)*	-1475.29 (0.013)*	-2106.89 (0.006)
Lockout11	-100.826 (0.705)	-231.362 (0.396)	-246.079 (0.398)	-216.644 (0.449)	-109.154 (0.739)	-41.834 (0.882)	-237.068 (0.411)	45.06373 (0.883)
AttendTrendFD	0.119579 (0.159)	0.124781 (0.182)	0.100958 (0.263)	0.093534 (0.321)	0.092060 (0.288)	0.093647 (0.246)	0.098716 (0.269)	0.111958 (0.171)
Adj. R-Squared	0.3771	0.4686	0.3347	0.3306	0.3571	0.4457	0.3320	0.4600

P-values in parentheses
*significant at the 5% level or better

The one inter-season competitive balance metric that is statistically significant in the NHL is the average number of years since each team in the league last qualified for the playoffs. The parameter estimate suggests that if the average number of years goes up by 1, average per-game attendance would increase by around 200 (about 1% of the current per-game attendance). Such a result provides some evidence that NHL fans may prefer to see the same teams qualify for the playoffs each year and thus prefer dynasties over competitive balance. If this result is valid, such a finding could perhaps be explained by the fact that certain teams (such as the Original Six) have far greater drawing power in the NHL and league-wide there is interest in seeing these teams have success at the expense of newer, less popular teams. However, since none of the other consecutive season competitive balance metrics were statistically significant this result may represent a Type I error. Taken altogether, these results do not provide much support for Hypothesis 2 that consecutive season competitive balance is an important driver of fan interest, a result that is discussed further in section 5.5.

5.3 Control Variables

In addition to the regression results concerning the independent variables of interest, there are also some important results in regards to the control variables (see Table 7 above for the results of all three leagues). First and foremost, despite economic theory guiding the selection of appropriate control variables, there are very few variables in each model that are statistically significant. This highlights the difficulty in explaining year-to-year aggregate attendance changes in professional sports. Although this may beg the question of why league-wide attendance was used as the dependent variable, it is important to remember that one of the primary contributions of this study is the investigation of the effects of competitive balance at the league level (see the Chapter 4 discussion on the dependent variable). To show that increasing the competitiveness of the playoff race benefits the teams that are directly competing for those spots is somewhat obvious and has been shown before. However, when taken as a whole, do those gains outweigh any potential losses in interest for other teams that have already secured playoff spots? Only an investigation at the league-level can show whether these considerations matter for all 30 teams as a collective. In addition, despite the difficulties in explaining league-wide attendance, the final models are still able to explain 40-60% of the variance in the change of average attendance per year.

Of the six categories of control variables, two (stadium capacity and real ticket prices) did not show statistically significant results for any of the leagues. This suggests that in the aggregate at the league-level, ticket prices and stadium capacity do not have large effects on attendance. Although certainly these variables would impact individual team attendance, these effects are small and get washed out when observed at the league-level. The same is true for franchise relocations and new stadiums as neither of these two variables were statistically significant for any of the leagues. The dummy variable for new franchises, however, was significant at the 5% level for both MLB and the NHL. For MLB, each new franchise led to an increase in average attendance per game of around 1,100 which shows that there is pent up demand for MLB franchises and that expansion can lead to greater fan interest. For the NHL, the reverse is true, as each new franchise is expected to decrease average attendance per game by about 300. This suggests that the NHL has over-expanded and in doing so has cost the league in terms of fan interest.

Other variables that show statistically significant results at the 5% level for one or more leagues include the seasonal competitive balance metric (NBA), strike/lockout dummies (MLB, NBA), and the attendance trend variable (NHL). Early specifications using the actual to idealized ratio of standard deviation of win percentages for the seasonal competitive balance metric (for either the final or mid-season standings), did not show significant results. However, that same metric applied to the middle third of teams in the final standings does give support to the idea that seasonal competitive balance is important in professional sports. For the NBA, each one unit increase in this metric, which represents a greater standard deviation of win percentages for the middle third of teams and thus less competitive balance, is expected to reduce average attendance per game by about 600. For MLB, this effect is even greater, although the parameter estimate is only significant at the 10% level. Each one unit increase in the competitive balance metric in MLB yields a reduction in average attendance per game of about 1,800. These results provide support at the league-level that the tightness of the playoff race is important for fan interest.

Most of the results for years affected by a strike or a lockout are not statistically significant, with two notable exceptions. First, the 1994 MLB players' strike had a significant negative impact on per-game attendance in the following season (since the strike canceled the second half of the 1994 season, the dummy variable was applied to 1995). This strike was responsible for a large per-game attendance reduction in the 1995 season of around 3,200. Similarly, the 1998 NBA lockout led to a reduction in average attendance per game of about 1,500 during the 1998-99 season. Although the effects of the 1994 MLB players strike and the 1998 NBA lockout had significant negative effects on fan interest, it is notable that the other six lockouts/strikes (1972 MLB strike, 1981 MLB strike, 2011 NBA lockout, 1994 NHL lockout, 2004 NHL lockout, and 2012 NHL lockout) did not have a significant effect on attendance. This is particularly noteworthy for the 2004 NHL lockout which led to the cancellation of the entire 2004-05 season.

These results concerning the effects of strikes and lockouts are mostly inconsistent with the findings of Schmidt and Berri (2004) which found that each strike and lockout in MLB, the NHL, and the NFL had a statistically significant negative effect on attendance for the year in question. However, the dependent variable used in their analysis is the average attendance per team, as opposed to the average attendance per game used in this study. Using average attendance per team as the dependent variable is essentially guaranteed to show significant negative results from strikes and lockouts due to the fact that these labor stoppages cause a lower number of games to be played in the strike/lockout affected season. This lower number of games will substantially reduce the average attendance per team for that season, but may have no actual effect on the average attendance per game.

Replicating the Schmidt and Berri (2004) time series analysis but using average attendance per game as the dependent variable finds that there are no statistically significant effects on attendance for any strike/lockout except for the 1994 MLB players' strike. Perhaps more noteworthy, replicating their analysis exactly but extending it to include the 2004-05 NHL lockout shows no statistically significant drop in attendance during the season following the lockout. This is due to the fact that the NHL played a full complement of games that season following the loss of the entire 2004-05 season which makes the average attendance per team dependent variable just a scaled measure of average attendance per game.

5.4 Alternate Models

The final regression models used for this study were determined through an iterative process that utilized various different specifications for the dependent variable as well as the set of control variables. In each case, the independent variables of interest for this process were the percentage of teams that qualify for the playoffs and its square term. For each model combination of one dependent variable specification and a given set of control variables, these same independent variables were used in order to maintain consistency as the models were expanded and enhanced. This allowed for one model specification to be chosen as the most effective at answering the research questions in addition to showcasing the robustness of the model to various specifications.

The first set of regression models used total league-wide attendance for a given league as the dependent variable. Early models using this specification suffered from significant multicollinearity problems due to several independent and control variables that exhibited monotonically increasing trends over the length of the data set that mirrored the general increasing trend of total league-wide attendance for each league. In particular, the number of teams in the league, the number of games per team, ticket prices, the U.S. population, and the U.S. per capita income are all highly correlated and thus affected the statistical reliability of the model. To address this issue, as well as to increase the number of degrees of freedom, the dependent variable was adjusted to absorb two of the control variables: the number of teams in the league and the number of games per team. Dividing total league-wide attendance by these two variables creates a second dependent variable that is the average attendance per game for a given league-year. This change significantly reduces the multicollinearity problems without jeopardizing the model. Although the number of teams in the league and the number of games per team are important controls that must be included in the model in some form, it is not necessary to get parameter estimates for these variables as the effect of increasing the number of teams or the number of games in a league should have a very predictable scalable positive effect on total attendance.

Two other dependent variable specifications were created by further absorbing control variables into the dependent variable. First, the control variable for stadium capacity was used to create the average attendance per game as a percentage of capacity. Second, the ticket price control was used to create the average attendance per game weighted by average ticket prices for each team. This ticket price weighted average attendance dependent variable was done solely for MLB because neither the NBA nor NHL has sufficient ticket price information to create a dependent variable in this manner with enough data points. This process of creating additional dependent variable specifications, similar to that done for total teams and games per team to create average attendance per game, frees up an additional degree of freedom while also allowing for additional specifications for robustness checks.

All of these dependent variable specifications were further considered as part of first difference models. The absolute average attendance models exhibit non-stationary effects that jeopardize the reliability of the statistical results from these models. As a result, additional models were created that used the first difference of all variables except the dummy variables. Dickey-fuller tests on the times series of the first difference of each of the average attendance dependent variable specifications show that the first difference data is stationary with a p-value of 0.000 for all leagues considered.

Moving to the control variables, different specifications were tested for stadium age, seasonal competitive balance, and the trend. For stadium age, the average age of all current stadiums is used as an introductory control variable for the stadium experience. However, this variable, as an average, may not accurately account for the important elements that drive interest in new stadiums. As a result, two additional specifications meant to capture stadium/franchise effects are utilized. The first specification breaks this variable into three dummy variables to account for three important stadium related components: new franchises (which often enter the league with new stadiums), franchise relocations to new cities (which often involve moving into new stadiums), and newly constructed/extensively renovated stadiums involving pre-existing teams in their current city. This new specification allows not only for direct measurement of a new stadium's effect on attendance but also the corresponding effects of new franchises and franchise relocations.

A further set of stadium variables builds on the previous dummy variable specification by accounting for the fact that the effect of new franchises, relocations, and new stadiums might last for a period of time longer than one year. In this case, the effect is modeled as lasting for three years. However, in consideration of the fact that the novelty effect of any of these three changes will likely diminish over time, this new specification assigns a value of one for the year immediately following one of these changes, a value of 0.67 for the second year, and a value of 0.33 for the third year. This alternate specification may more closely approximate the actual fan response to new franchises, relocations, and new stadiums, and also provides for an additional robustness check on the modeling of this control variable.

For seasonal competitive balance, the ratio of actual to idealized standard deviation of win percentages is used for each league-year as the introductory control variable. This metric was chosen due to its popularity in the literature for studies investigating the effect of seasonal competitive balance on fan interest/attendance. However, this variable may not adequately measure the level of competitive balance that exists throughout the season, or specifically in regards to the playoff race. As a result, two additional seasonal competitive balance metrics were considered.

First, a mid-seasonal ratio was calculated in an identical format except the mid-season standings (as opposed to the final standings) were used. This alternative measure looks at the level of dispersion in the standings mid-way through season, which could be a better measure of the effect of seasonal competitive balance on fan interest and attendance as the season is progressing. Mid-season standings were recorded for each league from shrpsports.com using July 1st as the mid-season point for MLB and January 15th as the mid-season point for both the NBA and the NHL. Those dates were chosen based on looking at the true mid-season (half of the season's games had been played) for each season of each league and then choosing a representative average that could serve as the approximate mid-point for every year of the league in question.

The second alternative seasonal competitive balance measure is a calculation of the final season ratio of actual to idealized standard deviation of win percentages for the middle third of the teams of each league. Although total dispersion of win percentages may be important, a better measure may be the dispersion of teams that are competitive for a playoff position down the stretch.

For the trend control variable, a proxy is needed to account for other unexplained factors that have contributed to the general rise in popularity of sports over the past 60 years. First, U.S. population and real per capita income were jointly used to model this observed increase in the demand for sports. Second, a new attendance trend variable was created that utilizes the average attendance in the other professional sport leagues as a control for the league in question.

Utilizing the different dependent variables and control variables described in this section allowed for several different model specifications to be run for each of the three leagues in order to determine the best performing base-line model that is also generally robust to different specifications. For each dependent variable (average attendance per game, average attendance as a percentage of capacity, average attendance per game weighted by ticket price, first difference of average attendance per game, first difference of average attendance as a percentage of capacity, first difference of average attendance per game weight by ticket price), eight specifications were run for each league that gradually built up the model from initial control variables to more detailed and refined control variables.

Overall, the results from these 112 model specifications (48 for MLB, 32 for the NBA and 32 for the NHL) are generally consistent, providing strong support for the robustness of the final base-line model used in this study. See Appendix B for the results of these various specifications. Although the models using the absolute measures of the dependent variable show extremely high adjusted R-squared values (up to 0.97 for MLB, 0.93 for the NHL, and 0.88 for the NBA), some of this fit is spurious and due to the non-stationary nature of the attendance time-series data. As mentioned previously, first differencing the data solves this problem (Dickey-Fuller tests reject the null hypothesis of a unit root in the first differenced attendance data series for each league with a p-value of 0.000), and so the final reported analysis utilized the first differenced models. Although these models show significantly lower adjusted R-squared values than the absolute models, they are still quite high, with values up to 0.59 for MLB, 0.43 for the NHL, and 0.39 for the NBA. These relatively high adjusted R-squared values for first differencing provide confidence in the explanatory power of the model.

For the three first differenced dependent variables (average attendance per game, average attendance per game as a percent of capacity, average attendance per game weighted by ticket price), the models generally show the greatest fit for the average attendance per game. This dependent variable is also the least complicated and easiest to understand, and also allows for parameter estimates to be obtained for the stadium capacity and real ticket price control variables. For these reasons, the dependent variable of first difference of average attendance per game was chosen for the final model. However, the magnitude, direction, and significance of the important results are largely unaffected by this choice.

For the control variables, the attendance trend was used over the U.S. population and per capita income variables due to multicollinearity concerns as well as the fact that the attendance trend represents a better proxy for the underlying demand for professional sports in the United States. The standard set of stadium dummy variables for new franchises, relocations, and new stadiums was chosen over the weighted average stadium dummies due to the fact that the standard dummies better resemble the expected fan response in a first difference model. The weighted average stadium dummies are a better approximation of the fan response in the absolute measures, but in first differencing they would suggest that a new stadium, for example, would generate a rise in attendance in year one, a further rise in year two, and an even further rise in year three. This is unlikely to be the case and it is therefore no surprise that the standard dummies generate higher fit in the first differencing models. In addition, both sets of dummies outperform the variable for average stadium age that was first considered.

The seasonal competitive balance measure for the middle third of teams is chosen over the standard seasonal measure as well as the mid-seasonal measure due to its better predictive ability in the models. In addition, this variable seems to better approximate what fans most respond to during a season, in that the closeness of teams that are vying for playoff spots is of the most importance for competitive balance concerns.

These are the factors that informed the choice of the final model that was used in this study to test the effect of playoff structure and consecutive season competitive balance on attendance. However, in all cases, the specific choice of control variables did not have large impacts on the results concerning the independent variables of interest. In addition, performing the same analyses on a subset of the data for each league (1969-2013 for MLB, 1979-2013 for the NHL, and 1982-2013 for the NBA) likewise did not significantly change the results. In consideration of all of these different specifications, there is confidence in the robustness of the model and in the significance of the findings.

5.5 Concluding Discussion

Taken together, the results from this study offer some important findings concerning competitive balance and its affect on fan interest. Although the newly proposed consecutive season competitive balance metrics largely did not show statistically significant effects on attendance at the league-level, this is perhaps not surprising. Trying to explain the factors that contribute to league-wide attendance changes proved to be a difficult task, as noted by the lack of significant results for many of the control variables that economic theory suggests would be important (such as ticket prices). Overall, the attendance series for each of the three studied leagues seemed to follow a general upward trend due to fundamental underlying factors driving interest in professional sports as a whole during the time frame examined. This is perhaps best appreciated by the fact that most of the lockouts and strikes included in the analysis had no affect on attendance, not even for the year in which they occurred. This suggests remarkable staying power for these leagues and the ability to rise above what otherwise should be large setbacks. Even the 1994 MLB players' strike, which had a well documented and severe effect on fan interest including an estimated loss of 3,200 fans per game based on this analysis, was overcome with no long-term attendance effects.

These observations highlight the unmistakable growing popularity of professional sports in recent decades and thus the difficulty in explaining attendance changes outside of this growing trend. Under the circumstances, the fact that 40-60% of the variance of average attendance in the first difference models was able to be explained by the control variables and the independent variables of interest is quite good. In addition, one of the primary variables of interest (playoff structure) was found to be a significant and importance driver of fan interest in MLB and NHL. This result, coupled with some significant results involving the seasonal competitive balance control variable for MLB and the NBA emphasizes the importance of a critical element of competitive balance that is most often overlooked in other studies: the playoffs. And in consideration of the difficulty of finding variables that have a statistically significant effect on league-wide attendance, this result is particularly impactful.

One of the primary theoretical contributions of this dissertation involves the idea that previous competitive balance studies have largely ignored the playoffs, despite the obvious importance of the playoffs to the fan experience. The results of this study overwhelming support the notion that the playoffs are important and are a crucial element of competitive balance studies. First and foremost, the results support hypothesis 1 in that the structure of the playoffs as determined by the percentage of teams that qualify for the postseason is an important consideration in terms of league-wide attendance. If it is assumed that major professional sport leagues are viewed and appreciated by fans in a somewhat similar fashion, at least at the margins, the results from the MLB and NHL analysis can be combined to suggest that there may be an optimal level for the percentage of teams that qualify for the playoffs (somewhere between 33% and 50%) that maximizes league-wide regular season attendance. Regardless of the exact figure (if there even is one), it is likely that MLB would be better off in terms of attendance by further increasing the number of teams that qualify for the playoffs whereas the NHL could drive higher attendance by doing the opposite. Specifically, the results show that if MLB were to increase the number of playoff teams to 12 it could expect a per game attendance increase of over 4,000 where if the NHL were to decrease the number of playoff teams to 14 it could expect a per game attendance increase of over 700, all else equal.

This result, untested and unproven in prior literature, supports the notion that increasing the number of playoff spots can increase the excitement as well as the number of teams involved in the playoff race, but only to a point. For low levels of playoff qualification, the positive effect of making more teams competitive for the postseason may outweigh the negative shift of importance from the regular season to the playoffs. However, for high levels of playoff qualification the opposite may be true, with fans of the best teams losing interest in the regular season due to having all but guaranteed a playoff spot early in the season. The idea that a simple structural change such as the number of teams that qualify for the playoffs could have such an important and positive effect on fan interest through competitive balance concerns is extremely noteworthy.

Much of the recent labor strife in professional sports can be traced at some level to the idea that competitive balance is important and that labor restrictions (salary caps/floors, luxury taxes, franchise tags, etc.) should be implemented to help foster competitive balance. Unfortunately, numerous previous studies have shown that these types of labor restrictions actually have no effect on competitive balance and thus create acrimonious owner/labor relationships with no notable increase in the appeal of the league for fans. Adjusting the playoff structure, however, gives a simple and efficient way to positively affect competitive balance and thus the fan experience, leading to increased league-wide attendance and profitability.

In the United States, MLB is most often the scapegoat when it comes to a perceived lack of competitive balance. Although previous studies have shown that in fact, by most measures MLB has relatively good levels of competitive balance compared with other leagues, this is not the fan perception. Perhaps the problem has been as simple as MLB has too few teams qualifying for the playoffs. Looking again at The Blue Ribbon Report that dissected MLB's competitive balance concerns shows that "proper competitive balance will not exist until every well-run club has a ***regularly recurring reasonable hope of reaching postseason play***" (Levin et. al. 2000, pg. 5, emphasis in original). Although completely evening the level of playing talent among all 30 MLB teams surely would accomplish this goal, an easier and more realistic task would be to just increase the number of teams that qualify for the playoffs. More playoff spots would directly increase the number of teams that reasonably had hope of reaching postseason play each year.

This idea that the playoff race is intertwined with fans' perceptions of competitive balance is further supported by the results from the seasonal competitive balance control variable. Using a standard seasonal competitive balance metric for the complete final standings and the complete mid-season standings did not show any statistically significant effects on attendance. However, when that variable measured only the middle third of teams at the end of the season (those most likely competing to make the playoffs), significant results were observed in line with the hypothesis that increased levels of competitive balance increase fan interest. When these results are taken together with those from the playoff structure and consecutive season competitive balance variables, a fuller picture of the importance of competitive balance emerges. Consistent with all of these results is the idea that it doesn't actually matter who wins and who loses a given match, a given season's championship, or a string of consecutive championships. All that matters is that your team is competitive.

In truth, this observation should be somewhat obvious in that it forms the core of the concept itself: *competitive* balance. But it seems to go against the very nature of sport itself, which celebrates winners and forgets losers. Yet, in consideration of the MLB's Blue Ribbon Report, competitiveness, win or lose, gives hope. And maybe hope is all that your average fan needs to stick by his/her team, attend games, and purchase merchandise. It doesn't matter if the Yankees win the World Series every year. It doesn't even matter if your team never makes the playoffs. All that matters is that your team is competitive down the stretch for one of those final playoff spots. Because if your team is competitive for a playoff spot, then there is reasonable hope of making the playoffs. And if your team makes the playoffs, then there is reasonable hope of winning the championship.

Thinking about the idea of competitive balance in this way (as opposed to the standard idea of wins and losses) fits with all of the results from this study. The only seasonal competitive balance control variable that affected attendance was the one that most closely measured the competitiveness of the playoff race. All of the consecutive season competitive balance measures were insignificant predictors of attendance, but they all focused on outcomes and not the level of competitiveness to reach the playoffs. And of course, the statistically significant effects of modifying the playoff structure directly impact the competitiveness of the playoff race due to the number of opportunities that exist to make the playoffs.

This interpretation of the meaning of competitive balance as viewed by the fan is at this point just a new theory, albeit one that is consistent with the results of this study. However, an alternate explanation may simply be that the effects of the consecutive season competitive balance measures got washed out in the aggregation of the data at the yearly level, a similar result that was seen for many of the control variables. For instance, the dummy variable for new stadiums was not significant for any of the models despite the fact that it is commonly accepted and shown that new stadiums often lead to a large bump in attendance the first year for specific teams (for example, the Baltimore Orioles saw an increase in attendance of over 12,000 per game in 1992 in their new stadium). However, the effect is not consistent across teams, with some teams/stadiums showing small increases or even decreases and when these effects are aggregated across all teams each year for a given league, the overall effect is small and difficult to assess properly. The result is an insignificant parameter estimate in the model at the league-level despite some importance for individual teams in certain situations.

Other control variables that did not show a statistically significant effect at the league level include stadium capacity, real ticket prices, franchise relocations, and most of the strikes/lockouts. Of course, for given teams and given years these variables would have important effects on attendance and that is why they were included as control variables. However, when aggregated at the league-level, there are no significant attendance responses based on changes in stadium capacity, average ticket prices or the location of franchises. Likewise, the effect of lockouts/strikes on attendance was largely insignificant at the league level which is a very important and interesting finding.

Of the eight strikes and lockouts investigated across the three leagues in this study, only two were shown to have a statistically significant negative effect on attendance. The first is the 1994 MLB strike which was notorious for causing the first cancellation of a postseason due to a work stoppage. The second is the 1998 NBA lockout which, in consideration of the lack of statistically significant findings for the other strikes and lockouts, could arguably be the result of Michael Jordan's second (and seemingly final) retirement from the Chicago Bulls and the NBA. If the observed drop in attendance during the 1998-99 season is thus largely or entirely attributed to the retirement of the Michael Jordan, then outside of the 1994 MLB strike, work stoppages do not have a significant effect on league attendance. This finding is especially noteworthy because it includes the 2004 NHL lockout which wiped out an entire season and seemingly did not adversely impact attendance in the NHL. These findings might inform the recent wave of league imposed lockouts in the NHL, NBA, and NFL during the previous three seasons, as there does not appear to be negative consequences for such actions.

A final interesting observation from the control variables concerns the addition of new franchises through expansion. The positive results for MLB follow the notion that professional sport leagues in the U.S. have monopoly power and use that to control entry in order to preserve excess demand and maintain pricing power. As a result, MLB currently has fewer teams than for which there is demand and therefore could benefit from further expansion. However, maintaining this excess demand may be more valuable to the league (e.g. through extracting sizable stadium subsidies) than the increased fan interest generated by expansion. Conversely, the negative results for the NHL suggest that the NHL has over-expanded and deteriorated interest in the league as a result. In particular, it is likely that expansion in the 1990's and early 2000s that put new franchises into cities in the Sun Belt (such as Atlanta, Miami and Nashville) that could not support their teams to the same extent as the established northern cities ended up pulling down league-wide attendance as a whole. The fact that the Atlanta team has already relocated to a smaller Canadian city (Winnipeg) furthers the notion that the Sun Belt expansion was not well founded and that the NHL could be a stronger and more popular league with fewer teams. The fact that these new franchise results for MLB and the NHL remained significant through the aggregation of the data at the league level showcases how strong these effects are on league attendance. Likewise, the fact that the primary results concerning the playoff percent variables are strongly significant highlights just how important the playoff structure must be for this effect to be observed in the league level model.

CHAPTER 6

CONCLUSION AND IMPLICATIONS

This dissertation sought to answer questions about how playoff structure and the level of consecutive season competitive balance impact fan interest in major professional sport leagues in the United States. The results suggest that playoff structure (namely the percentage of teams that qualify for the playoffs) is an important driver of fan interest as defined by the average attendance per game. Conversely, the level of consecutive season competitive balance as determined through various new metrics was not shown to be of significant importance to fans. The remainder of this chapter is divided into three parts. First, there are concluding remarks concerning the major findings of this research. Second, the implications for research and practice are discussed. Last, the limitations of this research are presented along with promising areas for future research.

6.1 Conclusion

This dissertation explored how playoff structure and various forms of consecutive season competitive balance influence league-wide attendance for MLB, the NHL, and the NBA. In contrast to previous literature in this field, this study suggests that playoffs are an important consideration that cannot be overlooked in competitive balance studies due to the inherent fan focus on postseason play. The results show that the percentage of teams that qualify for the playoffs is a significant driver of fan interest in MLB and the NHL as measured by attendance. Specifically it was shown that while early increases in the percentage of playoff qualifying teams in MLB led to decreased attendance, moving forward an increase of the playoffs to include 12 teams would be expected to increase per game attendance by over 4,000. Similarly, while playoff structural changes have a mixed history in the NHL, in the current situation a reduction in the number of playoff teams to 14 would be expected to increase the per game attendance by over 700. In addition, the combination of the results from these two leagues may support the idea that fan interest is maximized when the number of teams that make the playoffs falls within 33-50%. At such a potential optimal point, the competing concerns of increasing the number of teams that are competitive for a playoff spot and maintaining the importance of the regular season are balanced. Although the consecutive season competitive balance metrics did not significantly impact attendance, this result is consistent with the idea that fans care less about the actual outcome and more about the level of competitiveness, whether that is at the game, season, or consecutive season level. This idea is also consistent with the finding that the level of dispersion of the middle third of teams in a given year (those most likely to be actively competitive for a playoff spot) is a better predictor of attendance than similar seasonal competitive balance measures using all of the teams.

6.2 Implications

The results from this study concerning competitive balance have several implications for sport economics research. Most of the existing UOH literature focuses on match level or seasonal level outcomes, ignoring the playoffs. However, this study shows the importance of the playoffs as an important driver of fan interest. In the quest to find a competitive balance metric to which consumers show the greatest sensitivity, focusing on a playoff-based measure seems to be a good place to start. And although the newly proposed consecutive season competitive balance measures based on playoff outcomes were insignificant predictors of league-wide attendance, the theoretical contribution of this study suggests that inter-seasonal competitive balance concerns are at least as important as those for seasonal competitive balance. The difficulty of finding significant consecutive season results may simply lie in the aggregation of the data at the league level. Despite the fact that this league-wide approach limited the number of significant findings, ultimately the notion of competitive balance is important only at the league level and thus should be analyzed at this level.

This research also has important implications for professional sport league managers. The results show that simple manipulations of the playoff structure through the number of the teams that qualify for the playoffs can have substantial effects on fan interest and attendance. Such manipulations may be sufficient to satisfy underlying fan desire for competitive balance insomuch as more teams have a realistic hope of reaching postseason play. Leveling the playing field through labor restrictions may be unnecessary (not to mention challenging and acrimonious) as fans may care less about the actual outcomes and more about the perceived competitiveness of their favorite teams, win or lose.

Observing the differences in NCAA Division 1 men's basketball and FBS football may prove instructive in this manner. In both cases, the same small subset of teams wins the championship every year (e.g. UCLA, Kentucky, Indiana, North Carolina, Duke, UConn, Kansas, Louisville in basketball, and Alabama, Notre Dame, Oklahoma, USC, Miami, Nebraska, Ohio State, Texas in football), but the perceived level of balance in basketball is much higher. Every single team in Division 1 basketball has a legitimate chance at making the postseason tournament, as the winner of every conference is guaranteed a place. It doesn't seem to matter that most of those teams do not have a realistic chance of winning it all. Just making the tournament is a victory for many teams, whereas a sweet sixteen berth or a final four appearance may be as fulfilling for some teams as a championship is for others (e.g. George Mason making the final four in 2006 or Florida Gulf Coast making the sweet sixteen in 2013). This creates somewhat of tiered system of competitive balance where every team is competitive for a given noteworthy place.

The system in college football is the complete opposite, where 80% of the teams are shut out from national championship consideration before the season even starts (undefeated, non-championship seasons by teams such as Boise State and Utah emphasize this point). Although the bowl system seeks to replicate the idea that every team is competitive for something, the minor bowls are a sideshow to the national championship picture and there is no hope that any of those teams will ever have a George Mason style Cinderella run. Although the nature of the sport of football precludes a large March Madness style tournament, the results of this study suggest that FBS football would benefit from a larger playoff field in order to increase the number of teams that were competitive for the playoffs. Although FBS football is set to have four playoff teams for the first time in 2014, there is likely a long way to go until fan interest in maximized.

6.3 Limitations and Areas of Future Research

The major limitation of this study involves using attendance figures as a proxy for fan interest and league profitability. Since the rise in television viewing of professional sports, it can be questioned whether attendance figures truly give an adequate measure of demand (not to mention that there is an incentive for teams to upwardly misreport their attendance). However, attendance is regularly used in the sports economics literature as a trusted and accepted measure of fan demand. This seems reasonable because attendance has continued to increase in all of the major professional sport leagues despite the threat of television as well as a general increase in average ticket prices each year. This suggests that fan are still willing to pay for, and still value more highly, attending a game rather than watching it on TV. As a result, despite its drawbacks attendance is expected to be a good measure to test the effect of the variables of interest.

Additional limitations of this study relate to the completeness and quality of the data, which limits the overall generalizability of the conclusions. The initial conception of this study was to investigate all four of the major professional sport leagues in the U.S. (MLB, NFL, NHL, NBA) in order to build a common model that could explain the importance of playoff-based competitive balance measures for sport leagues as a whole. Unfortunately, the NFL attendance data suffers from a large proportion of sellouts, and the NBA data was too highly correlated with the independent variables of interest to provide reliable results concerning the hypotheses. Therefore, the analysis for MLB and the NHL largely formed the basis of the importance of the playoffs in terms of competitive balance and league-wide attendance. It is expected, though not proven, that the results from this analysis will generalize to the NBA and the NFL as well as other emerging professional leagues such as Major League Soccer and the Arena Football League.

Based on the previous limitations, it would be useful to extend this analysis to other leagues for confirmation of the results. In particular, it might be interesting to see whether the same general effects are present in other major professional leagues around the world. Just as consumers in other parts of the world have different tastes for food, fashion, and music, so too might consumers of sport in different countries have different tastes for competitive balance.

Future research might also find it fruitful to further test and validate the seasonal competitive balance measure used in this study. Although the ratio of actual to idealized standard deviation of win percentages is frequently used as the metric for competitive balance, this was shown to have no effect on attendance in this study. Instead, modifying the calculation slightly to include only the middle subset of teams (in this case the middle one third) may be a more salient measure of competitive balance actually experienced by consumers. The results of this study suggest that this measure is an important factor influencing attendance so future competitive balance studies should investigate this variable as a replacement for the current standard. If shown to be a robust measure of competitive balance to which consumers respond, then ACB studies could benefit from the inclusion of this variable in their historical analysis of the level of competitive balance present in the various professional sport leagues.

This dissertation has built on the work of previous literature concerning competitive balance in professional sports. While the goal was to introduce and attempt to answer questions related to how playoff structure and consecutive season competitive balance affect fan interest, the results from this work will also hopefully inspire future research investigating new elements of competitive balance. This is especially relevant moving forward since competitive balance continues to receive attention from the mainstream media as well as academic scholars.

APPENDIX A

HISTORY OF PLAYOFF QUALIFYING TEAMS

Number and Percentage of Playoff Qualifying Teams for each of the Big Four Leagues each Year

	MLB			NFL			NBA			NHL		
Year	Teams	Playoff Teams	Percent	Teams	Playoff Teams	Percent	Teams	Playoff Teams	Percent	Teams	Playoff Teams	Percent
1901	**16**	**0**	**0.0%**									
1902	**16**	**0**	**0.0%**									
1903	16	2	12.5%									
1904	16	2	12.5%									
1905	16	2	12.5%									
1906	16	2	12.5%									
1907	16	2	12.5%									
1908	16	2	12.5%									
1909	16	2	12.5%									
1910	16	2	12.5%									
1911	16	2	12.5%									
1912	16	2	12.5%									
1913	16	2	12.5%									
1914	16	2	12.5%									
1915	16	2	12.5%									
1916	16	2	12.5%									
1917	16	2	12.5%							4	2	50.0%
1918	16	2	12.5%							3	2	66.7%
1919	16	2	12.5%							4	2	50.0%
1920	16	2	12.5%	**14**	**0**	**0.0%**				4	2	50.0%
1921	16	2	12.5%	**21**	**0**	**0.0%**				4	2	50.0%
1922	16	2	12.5%	**18**	**0**	**0.0%**				4	2	50.0%
1923	16	2	12.5%	**20**	**0**	**0.0%**				4	2	50.0%
1924	16	2	12.5%	**19**	**0**	**0.0%**				6	3	50.0%
1925	16	2	12.5%	**20**	**0**	**0.0%**				7	3	42.9%
1926	16	2	12.5%	**22**	**0**	**0.0%**				10	6	60.0%
1927	16	2	12.5%	**12**	**0**	**0.0%**				10	6	60.0%
1928	16	2	12.5%	**10**	**0**	**0.0%**				10	6	60.0%
1929	16	2	12.5%	**12**	**0**	**0.0%**				10	6	60.0%
1930	16	2	12.5%	**11**	**0**	**0.0%**				10	6	60.0%
1931	16	2	12.5%	**10**	**0**	**0.0%**				8	6	75.0%
1932	16	2	12.5%	**8**	**0**	**0.0%**				9	6	66.7%
1933	16	2	12.5%	10	2	20.0%				9	6	66.7%
1934	16	2	12.5%	11	2	18.2%				9	6	66.7%

1935	16	2	12.5%	9	2	22.2%				8	6	75.0%
1936	16	2	12.5%	9	2	22.2%				8	6	75.0%
1937	16	2	12.5%	10	2	20.0%				8	6	75.0%
1938	16	2	12.5%	10	2	20.0%				**7**	**6**	**85.7%**
1939	16	2	12.5%	10	2	20.0%				**7**	**6**	**85.7%**
1940	16	2	12.5%	10	2	20.0%				**7**	**6**	**85.7%**
1941	16	2	12.5%	10	2	20.0%				**7**	**6**	**85.7%**
1942	16	2	12.5%	10	2	20.0%				6	4	66.7%
1943	16	2	12.5%	9	2	22.2%				6	4	66.7%
1944	16	2	12.5%	10	2	20.0%				6	4	66.7%
1945	16	2	12.5%	10	2	20.0%				6	4	66.7%
1946	16	2	12.5%	10	2	20.0%	11	6	54.5%	6	4	66.7%
1947	16	2	12.5%	10	2	20.0%	8	6	75.0%	6	4	66.7%
1948	16	2	12.5%	10	2	20.0%	12	8	66.7%	6	4	66.7%
1949	16	2	12.5%	10	2	20.0%	17	8	47.1%	6	4	66.7%
1950	16	2	12.5%	13	2	15.4%	11	8	72.7%	6	4	66.7%
1951	16	2	12.5%	12	2	16.7%	**10**	**8**	**80.0%**	6	4	66.7%
1952	16	2	12.5%	12	2	16.7%	**10**	**8**	**80.0%**	6	4	66.7%
1953	16	2	12.5%	12	2	16.7%	9	6	66.7%	6	4	66.7%
1954	16	2	12.5%	12	2	16.7%	8	6	75.0%	6	4	66.7%
1955	16	2	12.5%	12	2	16.7%	8	6	75.0%	6	4	66.7%
1956	16	2	12.5%	12	2	16.7%	8	6	75.0%	6	4	66.7%
1957	16	2	12.5%	12	2	16.7%	8	6	75.0%	6	4	66.7%
1958	16	2	12.5%	12	2	16.7%	8	6	75.0%	6	4	66.7%
1959	16	2	12.5%	12	2	16.7%	8	6	75.0%	6	4	66.7%
1960	16	2	12.5%	13	2	15.4%	8	6	75.0%	6	4	66.7%
1961	18	2	11.1%	14	2	14.3%	9	6	66.7%	6	4	66.7%
1962	20	2	10.0%	14	2	14.3%	9	6	66.7%	6	4	66.7%
1963	20	2	10.0%	14	2	14.3%	9	6	66.7%	6	4	66.7%
1964	20	2	10.0%	14	2	14.3%	9	6	66.7%	6	4	66.7%
1965	20	2	10.0%	14	2	14.3%	9	6	66.7%	6	4	66.7%
1966	20	2	10.0%	15	2	13.3%	**10**	**8**	**80.0%**	6	4	66.7%
1967	20	2	10.0%	16	4	25.0%	12	8	66.7%	12	8	66.7%
1968	20	2	10.0%	16	4	25.0%	14	8	57.1%	12	8	66.7%
1969	24	4	16.7%	16	4	25.0%	14	8	57.1%	12	8	66.7%
1970	24	4	16.7%	26	8	30.8%	17	8	47.1%	14	8	57.1%
1971	24	4	16.7%	26	8	30.8%	17	8	47.1%	14	8	57.1%
1972	24	4	16.7%	26	8	30.8%	17	8	47.1%	16	8	50.0%
1973	24	4	16.7%	26	8	30.8%	17	8	47.1%	16	8	50.0%
1974	24	4	16.7%	26	8	30.8%	18	10	55.6%	18	12	66.7%
1975	24	4	16.7%	26	8	30.8%	18	10	55.6%	18	12	66.7%
1976	24	4	16.7%	28	8	28.6%	22	12	54.5%	18	12	66.7%
1977	26	4	15.4%	28	8	28.6%	21	12	57.1%	18	12	66.7%
1978	26	4	15.4%	28	10	35.7%	22	12	54.5%	17	12	70.6%
1979	26	4	15.4%	28	10	35.7%	22	12	54.5%	21	16	76.2%

1980	26	4	15.4%	28	10	35.7%	23	12	52.2%	21	16	76.2%
1981	26	4	15.4%	28	10	35.7%	23	12	52.2%	21	16	76.2%
1982	26	4	15.4%	28	10	35.7%	23	12	52.2%	21	16	76.2%
1983	26	4	15.4%	28	10	35.7%	23	16	69.6%	21	16	76.2%
1984	26	4	15.4%	28	10	35.7%	23	16	69.6%	21	16	76.2%
1985	26	4	15.4%	28	10	35.7%	23	16	69.6%	21	16	76.2%
1986	26	4	15.4%	28	10	35.7%	23	16	69.6%	21	16	76.2%
1987	26	4	15.4%	28	10	35.7%	23	16	69.6%	21	16	76.2%
1988	26	4	15.4%	28	10	35.7%	25	16	64.0%	21	16	76.2%
1989	26	4	15.4%	28	10	35.7%	27	16	59.3%	21	16	76.2%
1990	26	4	15.4%	28	12	42.9%	27	16	59.3%	21	16	76.2%
1991	26	4	15.4%	28	12	42.9%	27	16	59.3%	22	16	72.7%
1992	26	4	15.4%	28	12	42.9%	27	16	59.3%	24	16	66.7%
1993	28	4	14.3%	28	12	42.9%	27	16	59.3%	26	16	61.5%
1994		Strike		28	12	42.9%	27	16	59.3%	26	16	61.5%
1995	28	8	28.6%	30	12	40.0%	29	16	55.2%	26	16	61.5%
1996	28	8	28.6%	30	12	40.0%	29	16	55.2%	26	16	61.5%
1997	28	8	28.6%	30	12	40.0%	29	16	55.2%	26	16	61.5%
1998	30	8	26.7%	30	12	40.0%	29	16	55.2%	27	16	59.3%
1999	30	8	26.7%	31	12	38.7%	29	16	55.2%	28	16	57.1%
2000	30	8	26.7%	31	12	38.7%	29	16	55.2%	30	16	53.3%
2001	30	8	26.7%	31	12	38.7%	29	16	55.2%	30	16	53.3%
2002	30	8	26.7%	32	12	37.5%	29	16	55.2%	30	16	53.3%
2003	30	8	26.7%	32	12	37.5%	29	16	55.2%	30	16	53.3%
2004	30	8	26.7%	32	12	37.5%	30	16	53.3%		Lockout	
2005	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2006	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2007	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2008	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2009	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2010	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2011	30	8	26.7%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2012	30	10	33.3%	32	12	37.5%	30	16	53.3%	30	16	53.3%
2013	30	10	33.3%	32	12	37.5%	30	16	53.3%	30	16	53.3%

APPENDIX B

REGRESSION RESULTS AND VARIABLE DEFINITIONS

Variable Definitions for Regression Results:

**Variable names with an "FD" at the end represent the first difference of that variable

Dependent Variables:

1. Average Attendance per Game is the total league-wide attendance for a given league divided by the total number of games played in a season.
2. Average Attendance per Game as a Percent of Capacity is the average attendance per game divided by the average capacity per game.
3. Average Attendance per Game Weighted by Ticket Price is the average attendance per game weighted by the average ticket price for each team
4. First Difference of the Average Attendance per Game is the first difference of the average attendance per game series
5. First Difference of the Average Attendance per Game as a Percent of Capacity is the first difference of the average attendance per game as a percent of capacity series.
6. First Difference of the Average Attendance per Game Weighted by Ticket Price is the first difference of the average attendance per game weighted by ticket price series.

Independent Variables:

1. PlayoffPct** is the percentage of teams that qualify for the playoffs in a given league-year.
2. PlayoffPct2** is the square of the percentage of teams that qualify for the playoffs in a given league-year.
3. POChurn** is the percentage of playoff qualifying teams in the current league-year that did not qualify for the playoffs the previous season.
4. POChurn3** is an average of the playoff churn for the previous three seasons.
5. POChurnW3** is a weighted average of the playoff churn for the previous three seasons, with the previous season given a weight of 1.0, the season prior to that given a weight of 0.67, and the season prior to that given a weight of 0.33.
6. CChurn** is a dummy variable equaling 1 if the current season saw a new champion and 0 if the current season was a repeat champion from the year prior.
7. SeasonChurn** is the adjusted churn of the final season standings compared with the mid-season standings. This value ranges from 0 to 1, with 0 representing identical final and mid-season standings and 1 representing complete churn (first to last, last to first, etc.)
8. AvgPOYears** is the average number of years since each team in a given league last reached the playoffs divided by the ideal average representing complete turnover in playoff teams every year.

Control Variables:

1. AvgCapacity** is the average stadium capacity per game for a given league-year.
2. RealTicketPrice** is the weighted average (by capacity) ticket price (in real 2013 dollars) for all teams in a given league-year.
3. AvgStadiumAge** is the average age (in years) of all current stadiums during a given league-year.
4. NewFranchise is an integer value of the number of new teams added to a league through expansion prior to a given year.
5. Relocation is an integer value of the number of teams that relocated to a new city prior to a given year.
6. NewStadium is an integer value of the number of teams that completed construction of a new stadium or the extensive renovation of their old stadiums prior to or during a given year.
7. NewFranchise3 assigns a value of 1 for the year following the addition of a new team to a league through expansion, a value of 0.67 for the second year after, and a value of 0.33 for the third year after.
8. Relocation3 assigns a value of 1 for the year following the relocation of a team to a new city, a value of 0.67 for the second year after, and a value of 0.33 for the third year after.
9. NewStadium3 assigns a value of 1 for the year following the completion of the construction of a team's new stadium or extensively renovated old stadium, a value of 0.67 for the second year after, and a value of 0.33 for the third year after.

10. SeasonalCB** is the ratio of actual to idealized standard deviation of win percentages in a given league-year. This is the most commonly used measure of the level of seasonal competitive balance in league.
11. MidSeasonalCB** is the ratio of actual to idealized standard deviation of win percentages calculated at the mid-point of the season (July 1st for MLB, January 15th for the NBA and the NHL).
12. CenSeasonalCB** is the ratio of actual to idealized standard deviation of win percentages calculated from the final standings for just the middle one third of the teams in the league (33rd to 67th percentile).
13. PopulationUS** is the population of the United States each year.
14. PerCapIncome** is the per capita income (in real 2012 dollars) for the United States each year.
15. AttendanceTrend** is the average attendance per game of the leagues not being considered in the current regression analysis. For the MLB regressions, AttendanceTrend is the average attendance per game of the NBA and NHL. For the NHL regressions, AttendanceTrend is the average attendance per game of the NBA and MLB. For the NBA regressions, AttendanceTrend is the average attendance per game of the MLB and NHL.
16. Strike72 is a dummy variable for the strike-affected 1972 MLB season.
17. Strike81 is a dummy variable for the strike-affected 1981 MLB season.
18. Strike94 is a dummy variable for the strike-affected 1994 MLB season. Since the second half of the 1994 season (including the playoffs) was completely canceled as a result of this strike, the variable takes a value of 1 for the 1995 MLB season.

19. Lockout94 is a dummy variable for the lockout-affected 1994-95 NHL season.
20. Lockout04 is a dummy variable for the lockout-affected 2004-05 NHL season. Since this lockout led to the complete cancellation of the 2004-05 NHL season, the variable takes a value of 1 for the 2005-06 NHL season.
21. Lockout12 is a dummy variable for the lockout-affected 2012-13 NHL season.
22. Lockout98 is a dummy variable for the lockout-affected 1998-99 NBA season.
23. Lockout11 is a dummy variable for the lockout-affected 2011-12 NBA season.

For each of these three leagues, the data for league-wide regular season attendance, number of teams, average ticket prices, number of games for each season, and the number of teams that qualify for the playoffs each year are obtained through the sport economist Rodney Fort's sport business data repository: https://sites.google.com/site/rodswebpages/codes. Rodney Fort is renowned in his field and his data repository is frequently used by other sport economists as a recognized source of high quality data. The original sources for Fort's attendance data include Quirk and Fort (1992), www.sports-reference.com, and ESPN. The original sources for Fort's ticket price data include The Sporting News and Team Marketing Report.

Data for playoff qualifying and advancing teams each year is obtained through the website www.sports-reference.com for each of the three leagues investigated and then the appropriate inter-season competitive balances measures are calculated using Excel. Data for U.S. population and per capita income were obtained from the U.S. Census Bureau (www.census.gov).

Table 13: MLB Regression Models: Dependent Variable Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPct	93188.64	66367.98	22011.69	-64925.2	-71421.6	-19798.2	-61970.7	-57751
	(0.020)*	(0.085)*	(0.441)	(0.028)*	(0.016)*	(0.013)*	(0.028)*	(0.047)*
PlayoffPct2	-162766	-67476.4	-46505.5	112157.5	121328.4		91854.14	83269.9
	(0.084)*	(0.477)	(0.505)	(0.128)	(0.096)*		(0.165)	(0.218)
AvgCapacity	1.549076	1.521181	0.337712	0.555122	0.497067	-0.07546	0.514995	0.52863
	(0.000)*	(0.000)*	(0.065)*	(0.023)*	(0.035)*	(0.440)	(0.031)*	(0.027)*
RealTicketPrice	1579.128	1384.002	222.7783	496.8302	480.8993		456.2824	460.682
	(0.000)*	(0.000)*	(0.235)	(0.010)*	(0.011)*		(0.022)*	(0.019)*
AvgStadiumAge	497.4356	454.1946	408.2858					
	(0.000)*	(0.000)*	(0.000)*					
NewFranchise				372.9448				
				(0.211)				
Relocation				137.5659				
				(0.851)				
NewStadium				-88.4652				
				(0.735)				
NewFranchise3					470.534	297.8236	366.2615	314.945
					(0.106)	(0.333)	(0.203)	(0.289)
Relocation3					-203.519	-82.9588	137.1578	261.133
					(0.773)	(0.914)	(0.844)	(0.729)
NewStadium3					-159.253	42.08467	-275.388	-273.63
					(0.497)	(0.863)	(0.276)	(0.253)
SeasonalCB		242.4707	115.9859	-599.080	-1066.64	-899.396		
		(0.772)	(0.838)	(0.534)	(0.346)	(0.464)		
MidSeasonalCB							165.1624	
							(0.901)	
CenSeasonalCB								648.779
								(0.663)
Strike72		-4770.03	-1659.03	-2149.84	-1390.69	-1102.16	-1676.53	-1924.8
		(0.013)*	(0.215)	(0.166)	(0.373)	(0.514)	(0.295)	(0.259)
Strike81		-6288.95	-965.153	1753.921	2124.217	3254.115	2871.454	2782.71
		(0.012)*	(0.588)	(0.400)	(0.297)	(0.104)	(0.177)	(0.182)
Strike94		-3584.19	-1603.49	-2666.11	-2704.00	-3214.82	-2040.55	-1969.4
		(0.083)*	(0.255)	(0.071)*	(0.069)*	(0.041)*	(0.183)	(0.199)
PopulationUS			0.000052					
			(0.272)					
PerCapIncome			0.584877					
			(0.026)*					
AttendanceTrend				2.081297	2.164358	2.567487	2.250017	2.23405
				(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
Adj. R-Squared	0.9198	0.9338	0.9700	0.9632	0.9648	0.9557	0.9608	0.9610

P-values in parentheses
*significant at the 10% level or better

Table 14: MLB Regression Models: Dependent Variable Average Attendance per Game as a Percent of Capacity

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPct	4.027763 (0.002)*	3.291366 (0.008)*	0.526971 (0.376)	-0.95556 (0.099)*	-1.11665 (0.056)*	0.015168 (0.448)	-0.90857 (0.124)	-0.7907 (0.203)
PlayoffPct2	-7.22229 (0.019)*	-4.92086 (0.110)	-1.05754 (0.462)	1.401137 (0.312)	1.714346 (0.215)		1.125068 (0.399)	0.85373 (0.544)
RealTicketPrice	0.016878 (0.000)*	0.013894 (0.000)*	0.007711 (0.000)*	0.010389 (0.000)*	0.011220 (0.000)*		0.010252 (0.000)*	0.01015 (0.000)*
AvgStadiumAge	0.002323 (0.203)	0.003171 (0.073)*	0.007974 (0.000)*					
NewFranchise				0.004628 (0.465)				
Relocation				-0.00062 (0.969)				
NewStadium				-0.00389 (0.494)				
NewFranchise3					0.007477 (0.236)	-0.00674 (0.449)	0.004595 (0.465)	0.00201 (0.756)
Relocation3					-0.00751 (0.623)	0.037214 (0.083)*	0.001611 (0.917)	0.00540 (0.745)
NewStadium3					-0.00573 (0.260)	0.010676 (0.123)	-0.00831 (0.139)	-0.0089 (0.097)*
SeasonalCB		-0.06906 (0.006)	-0.00161 (0.889)	-0.01977 (0.349)	-0.02914 (0.229)	0.035391 (0.302)		
MidSeasonalCB							-0.00587 (0.840)	
CenSeasonalCB								0.01927 (0.553)
Strike72		-0.12265 (0.048)*	-0.03835 (0.156)	-0.04239 (0.199)	-0.02791 (0.398)	-0.08650 (0.078)*	-0.03486 (0.311)	-0.0430 (0.237)
Strike81		-0.16440 (0.042)*	-0.01669 (0.641)	0.050599 (0.220)	0.050916 (0.210)	-0.02077 (0.710)	0.067053 (0.115)	0.06294 (0.131)
Strike94		-0.07768 (0.247)	-0.03944 (0.176)	-0.05801 (0.073)*	-0.05478 (0.092)*	-0.12712 (0.006)*	-0.04243 (0.211)	-0.0390 (0.249)
PopulationUS			1.11e-09 (0.233)					
PerCapIncome			0.000011 (0.044)*					
AttendanceTrend				0.000044 (0.000)*	0.000044 (0.000)*	0.000047 (0.000)*	0.000046 (0.000)*	0.00005 (0.000)*
Adj. R-Squared	0.8031	0.8428	0.9711	0.9656	0.9670	0.9196	0.9639	0.9642

P-values in parentheses
*significant at the 10% level or better

Table 15: MLB Regression Models: Dependent Variable Average Attendance per Game Weighted by Ticket Price

Independent Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
PlayoffPct	152522.6 (0.075)*	45807.5 (0.526)	15169.59 (0.627)	-45055.4 (0.168)	-51984.7 (0.111)	-26673.6 (0.004)*	-49091.0 (0.113)	-50700.6 (0.119)
PlayoffPct2	-152506 (0.452)	148631.7 (0.403)	-32337.9 (0.672)	52323.44 (0.519)	65590.18 (0.414)		48712.97 (0.499)	51608.35 (0.492)
AvgCapacity	0.329013 (0.074)*	0.594996 (0.001)*	0.082630 (0.289)	-0.10052 (0.365)	-0.12439 (0.310)	-0.16904 (0.124)	-0.06075 (0.586)	-0.06253 (0.583)
AvgStadiumAge	29.457 (0.810)	131.206 (0.202)	401.9201 (0.000)*					
NewFranchise				155.2004 (0.651)				
Relocation				175.0886 (0.841)				
NewStadium				238.4603 (0.432)				
NewFranchise3					469.4328 (0.171)	431.8108 (0.201)	485.0049 (0.135)	433.7118 (0.200)
Relocation3					-377.236 (0.653)	-411.872 (0.622)	200.7691 (0.799)	202.8171 (0.813)
NewStadium3					185.1297 (0.480)	202.8035 (0.436)	50.17173 (0.853)	20.70956 (0.937)
SeasonalCB		-1838.47 (0.240)	15.46564 (0.980)	-496.660 (0.664)	-1473.17 (0.273)	-1470.15 (0.271)		
MidSeasonalCB							-578.290 (0.695)	
CenSeasonalCB								-58.5037 (0.972)
Strike72		-5916.17 (0.100)*	-1458.15 (0.301)	-1398.07 (0.433)	-700.478 (0.700)	-870.514 (0.628)	-1045.15 (0.554)	-1096.30 (0.561)
Strike81		-20284.8 (0.000)*	-1193.36 (0.541)	3370.743 (0.163)	3577.46 (0.130)	4332.582 (0.048)*	4846.042 (0.040)*	4675.889 (0.045)*
Strike94		-10156.5 (0.009)*	-1874.41 (0.226)	-3667.10 (0.036)*	-3976.65 (0.024)*	-3618.92 (0.031)*	-3131.88 (0.068)*	-3089.95 (0.073)*
PopulationUS			0.000085 (0.069)*					
PerCapIncome			0.585887 (0.041)*					
AttendanceTrend				2.831647 (0.000)*	2.849528 (0.000)*	2.856268 (0.000)*	2.950598 (0.000)*	2.960339 (0.000)*
Adj. R-Squared	0.6714	0.7928	0.9688	0.9555	0.9576	0.9579	0.9572	0.9571

P-values in parentheses
*significant at the 10% level or better

Table 16: MLB Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-44218.4	-15834.1	-15547.6	-136511	-140136	-15027.6	-146731	-154082
	(0.199)	(0.640)	(0.650)	(0.001)*	(0.002)*	(0.025)*	(0.002)*	(0.001)*
PlayoffPct2FD	53089.21	-14161.4	13829.01	255488.6	260808.6		277609	298958.1
	(0.483)	(0.846)	(0.852)	(0.002)*	(0.005)*		(0.004)*	(0.002)*
AvgCapacityFD	0.378257	0.343346	0.400030	-0.01408	-0.26039	0.199832	-0.23223	-0.30569
	(0.062)*	(0.086)*	(0.065)*	(0.952)	(0.353)	(0.436)	(0.393)	(0.245)
RealTicketPriFD	35.18839	26.81555	23.6979	35.97851	57.48675	30.98582	-27.7122	-14.1976
	(0.520)	(0.605)	(0.653)	(0.370)	(0.181)	(0.501)	(0.904)	(0.948)
AvgStadAgeFD	73.77754	50.39642	94.04369					
	(0.517)	(0.645)	(0.446)					
NewFranchise				1061.758			889.7354	1133.058
				(0.001)*			(0.003)*	(0.000)*
Relocation				29.44014			866.9453	569.8633
				(0.962)			(0.314)	(0.491)
NewStadium				-69.9777			-2.31529	0.622449
				(0.731)			(0.993)	(0.998)
NewFranchise3					652.9566	317.3333		
					(0.005)*	(0.131)		
Relocation3					261.7057	-434.343		
					(0.619)	(0.407)		
NewStadium3					-252.176	-122.951		
					(0.137)	(0.493)		
SeasonalCBFD		53.59384	154.537	-942.700	-29.6292	-374.669		
		(0.918)	(0.772)	(0.169)	(0.961)	(0.574)		
MidSeasonCBFD							501.5733	
							(0.542)	
CenSeasonCBFD								-1876.32
								(0.059)*
Strike72		-885.537	-995.094	-898.797	-1097.81	-365.579	-1844.63	-1105.49
		(0.461)	(0.415)	(0.422)	(0.346)	(0.771)	(0.196)	(0.430)
Strike81		-1020.55	-1125.27	801.1162	1321.85	-244.774	1335.777	1493.813
		(0.532)	(0.501)	(0.560)	(0.402)	(0.881)	(0.411)	(0.332)
Strike94		-4955.9	-4905.12	-2512.68	-2834.49	-4484.9	-2949.43	-3229.08
		(0.002)*	(0.003)*	(0.061)*	(0.049)*	(0.003)*	(0.055)*	(0.029)*
PopulationUSFD			0.000153					
			(0.416)					
PerCapIncFD			0.229515					
			(0.497)					
AttendTrendFD				0.813860	0.904306	0.841107	0.391234	0.522442
				(0.033)*	(0.024)*	(0.055)*	(0.375)	(0.221)
Adj. R-Squared	0.2640	0.3541	0.3451	0.5680	0.5298	0.4455	0.5489	0.5910

P-values in parentheses
*significant at the 10% level or better

Table 17: MLB Regression Models: Dependent Variable First Difference of Average Attendance per Game as a Percent of Capacity

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model8
PlayoffPctFD	-0.88908 (0.205)	-0.29611 (0.675)	-0.32282 (0.650)	-2.22390 (0.003)*	-1.64771 (0.034)*	-0.25896 (0.045)*	-1.95993 (0.033)*	-2.01749 (0.025)*
PlayoffPct2FD	1.112199 (0.471)	0.284368 (0.853)	0.337064 (0.826)	4.160938 (0.008)*	2.976016 (0.068)*		3.701831 (0.055)*	3.900459 (0.040)*
RealTicketPriFD	0.000698 (0.538)	0.000579 (0.596)	0.000484 (0.661)	0.000662 (0.435)	0.000836 (0.357)	0.000633 (0.496)	-0.00176 (0.732)	-0.00154 (0.760)
AvgStadAgeFD	0.000780 (0.736)	0.000496 (0.825)	0.001329 (0.584)					
NewFranchise				0.018855 (0.002)*			0.015499 (0.018)*	0.018144 (0.005)*
Relocation				-0.00825 (0.483)			-0.00552 (0.728)	-0.01130 (0.490)
NewStadium				0.001168 (0.785)			0.005992 (0.294)	0.006154 (0.270)
NewFranchise3					0.008561 (0.053)*	0.005542 (0.184)		
Relocation3					-0.00616 (0.539)	-0.01073 (0.289)		
NewStadium3					-0.00186 (0.598)	-0.00087 (0.810)		
SeasonalCBFD		-0.00078 (0.943)	0.001089 (0.921)	-0.01893 (0.191)	-0.00176 (0.895)	-0.00795 (0.552)		
MidSeasonCBFD							0.003113 (0.865)	
CenSeasonCBFD								-0.02542 (0.252)
Strike72		-0.01828 (0.470)	-0.02111 (0.409)	-0.00820 (0.717)	-0.00942 (0.698)	-0.00579 (0.817)	-0.01097 (0.705)	0.001337 (0.965)
Strike81		-0.02412 (0.469)	-0.02362 (0.481)	-0.00517 (0.845)	-0.01050 (0.723)	-0.01492 (0.625)	-0.00605 (0.853)	-0.00759 (0.810)
Strike94		-0.09622 (0.004)*	-0.09503 (0.005)*	-0.05541 (0.048)*	-0.07355 (0.015)*	-0.08946 (0.003)*	-0.07287 (0.032)*	-0.07719 (0.021)*
PopulationUSFD			3.46e-09 (0.345)					
PerCapIncFD			5.59e-06 (0.429)					
AttendTrendFD				0.000017 (0.033)*	0.000019 (0.033)*	0.000017 (0.052)*	4.45e-06 (0.646)	5.94e-06 (0.536)
Adj. R-Squared	0.1959	0.2691	0.2681	0.4531	0.3753	0.3666	0.4322	0.4536

P-values in parentheses
*significant at the 10% level or better

Table 18: MLB Regression Models: Dependent Variable First Difference of Average Attendance per Game Weighted by Ticket Price

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-46581.3	-19331.0	-18444.2	-128672	-135822	-15419.5	-142491	-150640
	(0.187)	(0.587)	(0.610)	(0.003)*	(0.005)*	(0.028)*	(0.004)*	(0.002)*
PlayoffPct2FD	-57179.9	19461.06	17860.18	238098.7	251235.9		267508.7	290303.4
	(0.460)	(0.800)	(0.819)	(0.007)*	(0.010)*		(0.009)*	(0.004)*
AvgCapacityFD	0.364848	0.332815	0.394985	0.025066	-0.22534	0.211557	-0.23285	-0.31275
	(0.078)*	(0.111)	(0.083)*	(0.924)	(0.445)	(0.431)	(0.439)	(0.285)
AvgStadAgeFD	23.47908	11.63258	59.44349					
	(0.834)	(0.915)	(0.633)					
NewFranchise				954.3031			812.4451	1051.694
				(0.004)*			(0.014)*	(0.001)*
Relocation				-97.0381			883.401	555.261
				(0.890)			(0.324)	(0.523)
NewStadium				-8.79568			53.98414	61.18127
				(0.969)			(0.830)	(0.798)
NewFranchise3					689.2177	355.6822		
					(0.007)*	(0.126)		
Relocation3					15.04142	-612.343		
					(0.978)	(0.268)		
NewStadium3					-268.406	-159.546		
					(0.133)	(0.394)		
SeasonalCBFD		-68.8779	23.56854	-955.916	-358.676	-688.002		
		(0.899)	(0.966)	(0.219)	(0.591)	(0.338)		
MidSeasonCBFD							379.1606	
							(0.677)	
CenSeasonCBFD								-1973.14
								(0.074)*
Strike72		-930.393	-1009.32	-849.336	-919.557	-244.826	-1833.47	-1032.29
		(0.461)	(0.432)	(0.500)	(0.458)	(0.852)	(0.236)	(0.501)
Strike81		-1091.02	-1240.07	500.4444	875.5235	-606.077	1179.394	1302.034
		(0.525)	(0.481)	(0.747)	(0.600)	(0.724)	(0.511)	(0.445)
Strike94		-4535.03	-4486.23	-2350.94	-2579.91	-4133.75	-2631.82	-2923.82
		(0.007)*	(0.008)*	(0.114)	(0.088)*	(0.009)*	(0.113)	(0.067)*
PopulationUSFD			0.000161					
			(0.416)					
PerCapIncFD			0.156767					
			(0.656)					
AttendTrendFD				0.775845	0.804125	0.740683	0.258432	0.386837
				(0.068)*	(0.057)*	(0.105)	(0.582)	(0.395)
Adj. R-Squared	0.2696	0.3278	0.3188	0.4900	0.4718	0.3888	0.4725	0.5180

P-values in parentheses
*significant at the 10% level or better

Table 19: NHL Regression Models: Dependent Variable Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPct	-136382	-30575.2	-289620	-140120	-26347.0	-4336.87	-19176.5	-26525
	(0.505)	(0.850)	(0.070)*	(0.431)	(0.810)	(0.000)*	(0.885)	(0.809)
PlayoffPct2	116761	20980.36	260722.7	117122.6	10654.47		2052.223	10403.9
	(0.514)	(0.882)	(0.068)*	(0.452)	(0.913)		(0.986)	(0.915)
AvgCapacity	1.486745	0.401108	-1.70937	-0.40249	-0.61694	-0.08813	-0.66428	-0.5933
	(0.025)*	(0.495)	(0.052)*	(0.394)	(0.187)	(0.689)	(0.187)	(0.227)
RealTicketPrice	23.84968	17.22342	20.32685	14.08638	17.11049		15.25823	19.3576
	(0.204)	(0.297)	(0.203)	(0.428)	(0.307)		(0.358)	(0.213)
AvgStadiumAge	99.11264	62.86595	-125.732					
	(0.008)*	(0.051)*	(0.074)*					
NewFranchise				-127.577				
				(0.418)				
Relocation				258.6233				
				(0.212)				
NewStadium				-37.8434				
				(0.628)				
NewFranchise3					-246.097	-284.722	-283.088	-274.48
					(0.081)*	(0.000)*	(0.023)*	(0.018)*
Relocation3					346.5524	-349.462	302.1305	346.110
					(0.040)*	(0.043)*	(0.081)*	(0.041)*
NewStadium3					27.81334	122.1127	79.11876	28.6824
					(0.761)	(0.057)*	(0.466)	(0.756)
SeasonalCB		-888.327	-103.948	-624.660	-208.290	-665.104		
		(0.015)	(0.747)	(0.126)	(0.556)	(0.003)*		
MidSeasonalCB							1.748512	
							(0.996)	
CenSeasonalCB								-211.64
								(0.574)
Lockout94		-775.76	192.0465	-1130.45	-493.184	-482.809	-418.16	-357.95
		(0.059)*	(0.631)	(0.030)*	(0.276)	(0.369)	(0.167)	(0.304)
Lockout04		298.2585	265.2278	107.3378	16.39477	-87.7621	-51.6256	-73.063
		(0.306)	(0.221)	(0.703)	(0.931)	(0.865)	(0.815)	(0.713)
Lockout12		411.2097	199.4063	517.1658	252.6435	722.2608		200.935
		(0.159)	(0.564)	(0.034)*	(0.225)	(0.175)		(0.340)
PopulationUS			0.000028					
			(0.094)*					
PerCapIncome			0.278326					
			(0.035)*					
AttendanceTrend				0.255549	0.256939	0.214007	0.272557	0.25263
				(0.034)*	(0.006)*	(0.000)*	(0.004)*	(0.010)*
Adj. R-Squared	0.6930	0.8174	0.9120	0.8380	0.9299	0.9157	0.9001	0.9295

P-values in parentheses
*significant at the 10% level or better

Table 20: NHL Regression Models: Dependent Variable First Difference of Average Attendance per Game as a Percent of Capacity

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPct	-7.39701 (0.506)	-2.62434 (0.763)	-4.52770 (0.681)	-15.0210 (0.280)	-6.70089 (0.496)	-0.07119 (0.275)	-12.2847 (0.295)	-6.2009 (0.507)
PlayoffPct2	6.143192 (0.527)	2.124376 (0.780)	3.931069 (0.688)	13.25097 (0.275)	6.201042 (0.475)		11.1302 (0.289)	5.64122 (0.494)
RealTicketPrice	0.001333 (0.192)	0.000953 (0.286)	0.000959 (0.465)	0.000045 (0.973)	-0.00063 (0.620)		0.000193 (0.895)	-0.0001 (0.919)
AvgStadiumAge	0.004246 (0.005)*	0.004308 (0.004)*	0.003551 (0.175)					
NewFranchise				-0.00291 (0.809)				
Relocation				0.023917 (0.133)				
NewStadium				-0.00402 (0.514)				
NewFranchise3					0.001499 (0.863)	-0.01103 (0.010)*	-0.00422 (0.533)	-0.0045 (0.447)
Relocation3					0.030348 (0.029)*	-0.02723 (0.038)	0.024905 (0.095)*	0.02914 (0.028)*
NewStadium3					-0.01117 (0.082)*	0.004776 (0.310)	-0.00940 (0.222)	-0.0108 (0.070)*
SeasonalCB		-0.04214 (0.016)*	-0.03451 (0.181)	-0.03256 (0.287)	-0.04404 (0.145)	-0.04000 (0.017)*		
MidSeasonalCB							-0.03157 (0.270)	
CenSeasonalCB								-0.0493 (0.095)*
Lockout94		-0.03278 (0.079)*	-0.02273 (0.464)	-0.01999 (0.453)	-0.04609 (0.250)	0.016618 (0.670)	-0.00757 (0.736)	-0.0190 (0.516)
Lockout04		0.013397 (0.380)	0.011814 (0.507)	-0.00272 (0.901)	0.001004 (0.954)	-0.01279 (0.745)	0.001782 (0.931)	-0.0181 (0.268)
Lockout12		0.022652 (0.151)	0.035661 (0.118)	0.039776 (0.029)*	0.023583 (0.191)	0.045412 (0.264)		0.01454 (0.425)
PopulationUS			1.91e-10 (0.864)					
PerCapIncome			1.52e-06 (0.835)					
AttendanceTrend				0.000013 (0.137)	9.56e-06 (0.119)	1.47e-06 (0.300)	0.000013 (0.040)*	8.3e-06 (0.163)
Adj. R-Squared	0.4415	0.6696	0.5969	0.3613	0.6375	0.4625	0.4828	0.6727

P-values in parentheses
*significant at the 10% level or better

Table 21: NHL Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
PlayoffPctFD	-148296	-60159.4	-56569.1	-68101.7	-67279.3	93.28751	-56089.2	-60447.9
	(0.377)	(0.028)*	(0.046)*	(0.012)*	(0.031)*	(0.972)	(0.037)*	(0.019)*
PlayoffPct2FD	132620.2	49586.63	46986.93	55863.12	55296.86		46029.55	49518.87
	(0.371)	(0.027)*	(0.042)*	(0.011)*	(0.030)*		(0.036)*	(0.019)*
AvgCapacityFD	-1.15030	1.21585	1.209425	0.366321	1.027953	0.899247	0.381375	0.374380
	(0.146)	(0.000)*	(0.000)*	(0.317)	(0.010)*	(0.027)*	(0.311)	(0.328)
RealTicketPriFD	5.621903							
	(0.784)							
AvgStadAgeFD	-96.4362	116.1586	115.4329					
	(0.080)*	(0.000)*	(0.000)*					
NewFranchise				-324.328			-337.212	-332.230
				(0.000)*			(0.000)*	(0.000)*
Relocation				-112.852			-152.754	-138.758
				(0.565)			(0.445)	(0.482)
NewStadium				142.5199			121.4005	128.8015
				(0.134)			(0.213)	(0.188)
NewFranchise3					-161.298	-155.182		
					(0.013)*	(0.022)*		
Relocation3					-47.6254	-7.53462		
					(0.808)	(0.971)		
NewStadium3					18.24956	23.77416		
					(0.785)	(0.735)		
SeasonalCBFD		-2.98998	-6.00014	239.956	364.2401	176.4728		
		(0.990)	(0.980)	(0.327)	(0.190)	(0.522)		
MidSeasonCBFD							-167.489	
							(0.538)	
CenSeasonCBFD								-23.8569
								(0.907)
Lockout94		560.7413	552.5871	9.177541	404.8636	332.543	241.7914	-72.6770
		(0.305)	(0.322)	(0.986)	(0.508)	(0.604)	(0.709)	(0.890)
Lockout04		133.7103	96.50584	-233.490	-120.701	-57.7987	-97.6470	-172.056
		(0.803)	(0.871)	(0.668)	(0.850)	(0.931)	(0.863)	(0.754)
Lockout12		152.0619	1941.875	-16.4185	57.15372	65.83017		-0.64434
		(0.778)	(0.241)	(0.975)	(0.926)	(0.919)		(0.999)
PopulationUSFD			-4.0e-06					
			(0.956)					
PerCapIncFD			0.111366					
			(0.497)					
AttendTrendFD				0.283612	0.194056	0.174975	0.230257	0.245086
				(0.014)*	(0.129)	(0.190)	(0.044)*	(0.030)*
Adj. R-Squared	-0.0528	0.3904	0.3668	0.4351	0.2326	0.1525	0.4329	0.4207

P-values in parentheses
*significant at the 10% level or better

Table 22: NHL Regression Models: Dependent Variable First Difference of Average Attendance per Game as a Percent of Capacity

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-1.33052 (0.903)	-3.58417 (0.037)*	-3.35631 (0.059)*	-4.52866 (0.008)*	-4.17161 (0.032)*	0.005724 (0.972)	-3.68031 (0.033)*	-3.93461 (0.017)*
PlayoffPct2FD	1.085207 (0.910)	2.951888 (0.036)*	2.787474 (0.054)*	3.714835 (0.008)*	3.429443 (0.031)*		3.018755 (0.032)*	3.222335 (0.017)*
RealTicketPriFD	0.000036 (0.980)							
AvgStadAgeFD	0.000940 (0.649)	0.007605 (0.000)*	0.007559 (0.000)*					
NewFranchise				-0.01916 (0.000)*			-0.02012 (0.000)*	-0.01988 (0.000)*
Relocation				-0.01050 (0.391)			-0.01324 (0.291)	-0.01208 (0.330)
NewStadium				0.005824 (0.294)			0.00447 (0.433)	0.004627 (0.411)
NewFranchise3					-0.01081 (0.009)*	-0.01036 (0.015)*		
Relocation3					-0.00133 (0.911)	-0.00033 (0.998)		
NewStadium3					-0.00154 (0.709)	0.001592 (0.713)		
SeasonalCBFD		0.000234 (0.988)	0.000083 (0.996)	0.018605 (0.234)	0.026390 (0.133)	0.014696 (0.398)		
MidSeasonCBFD							-0.00960 (0.581)	
CenSeasonCBFD								-0.00497 (0.695)
Lockout94		0.037840 (0.276)	0.037297 (0.292)	-0.00104 (0.975)	0.026179 (0.498)	0.021499 (0.595)	0.015990 (0.695)	-0.00778 (0.817)
Lockout04		0.003306 (0.922)	0.000808 (0.983)	-0.01374 (0.690)	-0.01293 (0.747)	-0.00807 (0.848)	-0.00477 (0.894)	-0.00972 (0.780)
Lockout12		0.004844 (0.888)	0.070626 (0.482)	-0.00098 (0.977)	-0.00116 (0.976)	0.000633 (0.988)		-0.00059 (0.986)
PopulationUSFD			-2.3e-10 (0.960)					
PerCapIncFD			7.23e-06 (0.487)					
AttendTrendFD				0.000015 (0.031)*	0.000013 (0.097)*	0.000011 (0.169)	0.000011 (0.099)*	0.000012 (0.075)*
Adj. R-Squared	-0.3009	0.2848	0.2582	0.3331	0.1106	0.0214	0.3224	0.3110

P-values in parentheses
*significant at the 10% level or better

Table 23: NBA Regression Models: Dependent Variable Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPct	-344781 (0.331)	-252024 (0.537)	-353190 (0.438)	345476.8 (0.496)	573193.4 (0.332)	-3970.46 (0.066)*	691648.6 (0.191)	841870 (0.076)*
PlayoffPct2	289087.3 (0.363)	206755.2 (0.572)	299035.8 (0.459)	-319864 (0.480)	-526878 (0.319)		-633007 (0.181)	-763891 (0.072)*
AvgCapacity	0.051135 (0.678)	0.127400 (0.463)	0.116612 (0.511)	0.186319 (0.258)	0.079672 (0.634)	0.191958 (0.014)*	0.038046 (0.810)	0.18976 (0.239)
RealTicketPrice	-12.0462 (0.460)	-8.36737 (0.652)	-6.29583 (0.776)	-31.1821 (0.144)	-41.4605 (0.216)		-44.9195 (0.136)	-46.418 (0.063)*
AvgStadiumAge	-45.0198 (0.447)	-11.2408 (0.880)	-53.1904 (0.587)					
NewFranchise				338.6087 (0.062)*				
Relocation				-137.585 (0.383)				
NewStadium				43.31886 (0.350)				
NewFranchise3					147.6985 (0.482)	329.1997 (0.033)*	62.82959 (0.723)	50.3909 (0.741)
Relocation3					-197.441 (0.274)	-45.2075 (0.855)	-132.763 (0.451)	-201.13 (0.205)
NewStadium3					42.16419 (0.659)	291.1153 (0.007)*	57.83292 (0.544)	12.1605 (0.876)
SeasonalCB		-42.3775 (0.879)	-171.635 (0.617)	-310.163 (0.220)	-431.921 (0.133)	-268.012 (0.445)		
MidSeasonalCB							-480.579 (0.225)	
CenSeasonalCB								-530.11 (0.039)*
Lockout98		-388.793 (0.479)	-365.218 (0.568)	-616.254 (0.155)	-599.305 (0.227)	-289.765 (0.759)	-1279.38 (0.038)*	-886.34 (0.079)*
Lockout11		-202.268 (0.559)	-370.459 (0.331)	-327.598 (0.267)	-509.258 (0.155)	-362.621 (0.703)	-622.116 (0.143)	-480.83 (0.107)
PopulationUS			0.000025 (0.278)					
PerCapIncome			-0.15412 (0.219)					
AttendanceTrend				0.258752 (0.038)*	0.283770 (0.034)*	0.945824 (0.000)*	0.305349 (0.027)*	0.32721 (0.007)*
Adj. R-Squared	0.7352	0.6954	0.6893	0.8009	0.7901	0.9583	0.7844	0.8331

P-values in parentheses
*significant at the 10% level or better

Table 24: NBA Regression Models: Dependent Variable Average Attendance per Game as a Percent of Capacity

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPct	-75.2753 (0.016)*	-27.0753 (0.388)	-35.9179 (0.323)	-31.6429 (0.411)	-40.3276 (0.381)	-0.21635 (0.158)	-18.4054 (0.677)	23.7224 (0.512)
PlayoffPct2	66.98022 (0.017)*	23.86202 (0.395)	31.54592 (0.327)	28.19854 (0.409)	36.08307 (0.379)		16.54753 (0.674)	-21.048 (0.513)
RealTicketPrice	-0.00229 (0.131)	-0.00108 (0.450)	-0.00067 (0.705)	-0.00129 (0.450)	0.000236 (0.932)		-0.00097 (0.716)	-0.0022 (0.262)
AvgStadiumAge	-0.00761 (0.167)	0.001512 (0.792)	0.009801 (0.899)					
NewFranchise				0.031736 (0.029)*				
Relocation				-0.00369 (0.776)				
NewStadium				0.001827 (0.634)				
NewFranchise3					0.028548 (0.119)	0.022953 (0.039)*	0.016100 (0.330)	0.00930 (0.462)
Relocation3					-0.00877 (0.584)	-0.00157 (0.929)	-0.00270 (0.870)	-0.0109 (0.400)
NewStadium3					-0.00393 (0.640)	0.012350 (0.102)	-0.00151 (0.864)	-0.0032 (0.613)
SeasonalCB		-0.02312 (0.263)	-0.03320 (0.214)	-0.02839 (0.173)	-0.03035 (0.229)	0.015577 (0.507)		
MidSeasonalCB							-0.03796 (0.304)	
CenSeasonalCB								-0.0518 (0.009)*
Lockout98		-0.09150 (0.012)*	-0.09863 (0.029)*	-0.08464 (0.008)*	-0.09558 (0.018)*	-0.05563 (0.418)	-0.10532 (0.011)*	-0.1135 (0.002)*
Lockout11		-0.02036 (0.445)	-0.02748 (0.366)	-0.01937 (0.428)	-0.01681 (0.585)	-0.00707 (0.918)	-0.02733 (0.479)	-0.0248 (0.299)
PopulationUS			8.17e-10 (0.645)					
PerCapIncome			-7.50e-06 (0.447)					
AttendanceTrend				8.99e-06 (0.334)	6.64e-06 (0.521)	0.000043 (0.000)*	9.91e-06 (0.389)	0.00002 (0.066)*
Adj. R-Squared	0.3768	0.5271	0.4770	0.6365	0.5529	0.8806	0.5520	0.6954

P-values in parentheses
*significant at the 10% level or better

Table 25: NBA Regression Models: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-426922 (0.218)	-443741 (0.204)	-3187098 (0.183)	83992.64 (0.695)	-278190 (0.470)	857.4575 (0.643)	119062.5 (0.621)	-32554.6 (0.855)
PlayoffPct2FD	369301.1 (0.228)	380225.5 (0.217)	2777411 (0.184)		226711.6 (0.507)			
AvgCapacityFD	0.108636 (0.369)	0.021719 (0.862)	0.041173 (0.752)	-0.00208 (0.988)	-0.05837 (0.667)	0.006694 (0.926)	0.046942 (0.749)	0.103778 (0.348)
RealTicketPriFD	-10.8639 (0.571)	22.05495 (0.391)	17.64636 (0.504)	10.59618 (0.758)	-5.77110 (0.854)		4.988469 (0.892)	21.62952 (0.438)
AvgStadAgeFD	-86.2186 (0.136)	-34.8841 (0.582)	-37.1285 (0.568)					
NewFranchise				292.4146 (0.203)			2583.924 (0.586)	-454.583 (0.897)
Relocation				-77.1184 (0.720)			-100.018 (0.662)	-34.9552 (0.834)
NewStadium				41.24658 (0.483)			27.99275 (0.662)	38.86651 (0.407)
NewFranchise3					-205.656 (0.334)	51.4742 (0.479)		
Relocation3					-317.12 (0.127)	-59.8978 (0.620)		
NewStadium3					-29.0179 (0.527)	-3.19254 (0.952)		
SeasonalCBFD		-358.319 (0.168)	-369.269 (0.166)	-415.905 (0.155)	-371.715 (0.149)	-139.611 (0.459)		
MidSeasonCBFD							178.4109 (0.633)	
CenSeasonCBFD								-587.152 (0.012)*
Lockout98		-1051.97 (0.066)*	-1107.43 (0.080)*	-1062.86 (0.077)*	-1123.69 (0.041)*	-799.248 (0.157)	-1028.54 (0.094)*	-1490.74 (0.008)*
Lockout11		-231.812 (0.454)	-380.257 (0.268)	-277.357 (0.410)	-546.843 (0.114)	-363.973 (0.478)	27.31281 (0.826)	-223.605 (0.392)
PopulationUSFD			-0.00039 (0.232)					
PerCapIncFD			0.046485 (0.741)					
AttendTrendFD				0.047134 (0.590)	0.027239 (0.727)	-0.02860 (0.732)	-0.02643 (0.826)	0.096560 (0.248)
Adj. R-Squared	0.3396	0.1789	0.1835	0.0725	0.2515	-0.1108	0.1140	0.3970

P-values in parentheses
*significant at the 10% level or better

Table 26: NBA Regression Models: Dependent Variable First Difference of Average Attendance per Game as a Percent of Capacity

Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PlayoffPctFD	-38.4409	-36.4626	-335.734	20.79703	-34.4425	0.011643	21.5959	9.564638
	(0.233)	(0.322)	(0.185)	(0.372)	(0.448)	(0.947)	(0.360)	(0.646)
PlayoffPct2FD	34.29648	32.57564	294.0624		29.08353			
	(0.228)	(0.316)	(0.184)		(0.471)			
RealTicketPriFD	-0.00086	-0.00098	-0.00155	0.001441	0.002309		0.001592	0.002702
	(0.634)	(0.712)	(0.572)	(0.703)	(0.533)		(0.662)	(0.406)
AvgStadAgeFD	-0.01089	-0.01082	-0.01117					
	(0.036)*	(0.093)*	(0.094)					
NewFranchise				-0.01021			0.426232	0.185888
				(0.656)			(0.360)	(0.652)
Relocation				0.014893			0.013480	0.016319
				(0.516)			(0.535)	(0.393)
NewStadium				0.007631			0.007426	0.007722
				(0.225)			(0.224)	(0.146)
NewFranchise3					-0.03808	0.002342		
					(0.105)	(0.733)		
Relocation3					0.011696	0.000260		
					(0.583)	(0.982)		
NewStadium3					0.004195	-0.00154		
					(0.415)	(0.759)		
SeasonalCBFD		0.007534	0.007434	-0.00323	0.005905	0.005689		
		(0.767)	(0.775)	(0.914)	(0.832)	(0.745)		
MidSeasonCBFD							0.007673	
							(0.835)	
CenSeasonCBFD								-0.04282
								(0.083)*
Lockout98		0.008292	0.016321	-0.02046	-0.03191	-0.02209	-0.01426	-0.08957
		(0.877)	(0.780)	(0.733)	(0.585)	(0.676)	(0.817)	(0.119)
Lockout11		0.010287	-0.00931	0.009808	0.003736	-0.00928	0.017542	0.002286
		(0.749)	(0.797)	(0.782)	(0.920)	(0.848)	(0.711)	(0.939)
PopulationUSFD			-4.1e-08					
			(0.231)					
PerCapIncFD			-7.2e-06					
			(0.632)					
AttendTrendFD				-3.9e-06	1.35e-06	4.03e-06	-7.1e-06	1.51e-06
				(0.677)	(0.886)	(0.607)	(0.546)	(0.873)
Adj. R-Squared	0.0822	-0.1157	-0.1454	-0.3175	-0.2529	-0.1654	-0.3256	0.0093

P-values in parentheses
*significant at the 10% level or better

Table 27: H1 Final Regression Models, Subset: Dependent Variable First Difference of Average Attendance per Game

Independent Variable	MLB Model 1	MLB Model 2	NHL (1979-2012) Model 1	NHL (1979-2012) Model 2	NBA Model 1	NBA Model 2
PlayoffPctFD		-156950 (0.001)*		-41074.5 (0.390)		1124.393 (0.586)
PlayoffPct2FD		302537.8 (0.002)*		33804.46 (0.328)		
AvgCapacityFD	0.022403 (0.946)	-0.55468 (0.085)	0.310811 (0.332)	0.337372 (0.319)	-0.16447 (0.105)	-0.16139 (0.119)
RealTicketPriFD	-345.632 (0.207)	-117.676 (0.622)	-16.4925 (0.346)	-19.0298 (0.226)	23.15256 (0.362)	21.62952 (0.438)
NewFranchise	566.7245 (0.044)*	1159.522 (0.000)*	-4.09273 (0.961)	-42.2438 (0.697)	336.0822 (0.005)*	367.9293 (0.007)*
Relocation	524.8115 (0.783)	2294.691 (0.179)	232.1095 (0.248)	268.2343 (0.168)	-81.0359 (0.618)	-63.9270 (0.704)
NewStadium	79.00202 (0.799)	-249.144 (0.377)	9.116865 (0.910)	-12.0888 (0.878)	-15.2248 (0.767)	-9.52549 (0.858)
CenSeasonCBFD	-1477.45 (0.206)	-1848.99 (0.077)	-212.101 (0.320)	-231.057 (0.263)	-493.771 (0.008)*	-496.289 (0.009)*
Strike72	-948.902 (0.676)	-2730.64 (0.174)				
Strike81	-2438.88 (0.076)	1436.668 (0.368)				
Strike94	-6660.24 (0.000)*	-2883.28 (0.054)				
Lockout94			176.8094 (0.627)	162.4826 (0.641)		
Lockout04			60.81277 (0.875)	21.40535 (0.954)		
Lockout12			122.7725 (0.735)	91.04904 (0.794)		
Lockout98					-1373.30 (0.004)*	-1358.85 (0.005)*
Lockout11					-390.607 (0.274)	-372.482 (0.307)
AttendTrendFD	-0.81909 (0.336)	-0.35844 (0.643)	0.151235 (0.091)	0.155415 (0.073)	0.145614 (0.051)	0.147084 (0.054)
Adj. R-Squared	0.4377	0.6196	0.1862	0.2596	0.4383	0.4191

P-values in parentheses
*significant at the 5% level or better

BIBLIOGRAPHY

Baimbridge, M. (1998). Outcome uncertainty in sporting competition: the Olympic Games 1896–1996. *Applied Economics Letters*, *5*(3), 161-164.

Balfour, A. & Porter, P. K. (1991). The reserve clause in professional sports: legality and effect on competitive balance. *Labor Law Journal*, 42(1), 8-18.

Bennett, R. W., & Fizel, J. L. (1995). Telecast deregulation and competitive balance. *American Journal of Economics and Sociology*, *54*(2), 183-199.

Benz, M. A., Brandes, L., & Franck, E. (2009). Do Soccer associations really spend on a good thing? Empirical evidence on heterogeneity in the consumer response to match uncertainty of outcome. *Contemporary Economic Policy*, *27*(2), 216-235.

Berkowitz, J., Depken, C., & Wilson, D. (2011). When going in circles is going backward: outcome uncertainty in NASCAR. *Journal of Sports Economics*, 12(3), 253-283.

Berri, D., Brook, S., Frick, B., Fenn, A., & Vincente-Mayoral, R. (2005). The short supply of tall people: competitive imbalance and the National Basketball Association. *Journal of Economic Issues*, 39, 1029-1041.

Bishop, G. (2012). A five month season boils down to one. The New York Times. Retrieved from http://www.nytimes.com/2012/12/13/sports/ncaabasketball/march-madness-makes-basketballs-regular-season-seem-irrelevant.html?pagewanted=all&_r=1&

Booth, R. (2004). The economics of achieving competitive balance in the Australian Football League, 1897–2004. *Economic Papers: A journal of applied economics and policy*, *23*(4), 325-344.

Borland, J. (1987). The demand for Australian rules football. *The Economic Record*. 220-30.

Bowman, R. A., Lambrinos, J., & Ashman, T. (2012). Competitive Balance in the Eyes of the Sports Fan: Prospective Measures Using Point Spreads in the NFL and NBA. *Journal of Sports Economics*.

Bowman, R. A., Ashman, T., & Lambrinos, J. (2013). Prospective measures of competitive balance: application to money lines in major league baseball. *Applied Economics*, *45*(29), 4071-4081.

Brandes, L., & Franck, E. (2007). Who Made Who-An Empirical Analysis of Competitive Balance in European Soccer Leagues. *Eastern Economic Journal*, *33*(3), 379.

Buraimo, B., & Simmons, R. (2008). Do sports fans really value uncertainty of outcome? Evidence from the English premier league. *International Journal of Sport Finance*, *3*(3), 146-155.

Buraimo, B., & Simmons, R. (2009). A tale of two audiences: Spectators, television viewers and outcome uncertainty in Spanish football. *Journal of Economics and Business*, *61*(4), 326-338.

Butler, M. R. (1995). Competitive balance in major league baseball. *American Economist*, 39, 46-52.

Cairns, J. A. (1987). Evaluation changes in league structure: The reorganization of the Scottish football league. *Applied Economics*, 19, 259-261.

Carmichael, F., Millington, J., & Simmons, R. (1999). Elasticity of demand for Rugby League attendance and the impact of BskyB. *Applied Economics Letters*, *6*(12), 797-800.

Chang, Y. M., & Sanders, S. (2009). Pool Revenue Sharing, Team Investments, and Competitive Balance in Professional Sports A Theoretical Analysis. *Journal of Sports Economics*, *10*(4), 409-428.

Coates, D., & Humphreys, B. R. (2012). Game Attendance and Outcome Uncertainty in the National Hockey League. *Journal of Sports Economics*, *13*(4), 364-377.

Corral, J. (2009). Competitive balance and match uncertainty in grand-slam tennis: Effects of seeding system, gender, and court surface. *Journal of Sports Economics*, 10(6), 563-581.

Croix, S. J. L., & Kawaura, A. (1999). Rule changes and competitive balance in Japanese professional baseball. *Economic Inquiry*, *37*(2), 353-368.

Crooker, J., & Fenn, A. (2007). Sports leagues and parity: When league parity generates fan enthusiasm. *Journal of Sports Economics*, 8(2), 139-164.

Czarnitzki, D., & Stadtmann, G. (2002). Uncertainty of outcome versus reputation: Empirical evidence for the First German Football Division. *Empirical Economics*, *27*(1), 101-112.

Dawson, A., & Downward, P. (2005). Measuring Short-Run Uncertainty of Outcome in Sporting Leagues A Comment. *Journal of Sports Economics*, *6*(3), 303-313.

Depken, C. A. (1999). Free agency and the competitiveness of major league baseball. *Review of Industrial Organization*, 14, 205-217.

Depken, C. A., & Wilson, D. P. (2006). NCAA enforcement and competitive balance in college football. *Southern Economic Journal*, 826-845.

Dietl, H., Lang, M., & Werner, S. (2010). The effect of luxury taxes on competitive balance, club profits, and social welfare in sports leagues.*International Journal of Sport Finance*, *5*(1), 41-51.

Dietl, H. M., Grossmann, M., & Lang, M. (2011). Competitive balance and revenue sharing in sports leagues with utility-maximizing teams. *Journal of Sports Economics*, *12*(3), 284-308.

Dietl, H. M., Lang, M., & Rathke, A. (2011). The combined effect of salary restrictions and revenue sharing in sports leagues. *Economic Inquiry*, *49*(2), 447-463.

Dittmore, S. W., & Crow, C. M. (2010). The Influence of the Bowl Championship Series on Competitive Balance in College Football. *Journal of Sport Administration & Supervision*, *2*(1), 7-19.

Du Bois, C., & Heyndels, B. (2007). It's a different game you go to watch: Competitive balance in men's and woman's tennis. *European Sport Management Quarterly*, 7, 167-185.Eckard, E. W. (1998). The NCAA cartel and competitive balance in college football. *Review of Industrial Organization*, *13*(3), 347-369.

Eckard, E. (2001). Free agency, competitive balance, and diminishing returns to pennant contention. *Economic Inquiry*, 39(3), 430-443.

Eckard, E. W. (2003). The ANOVA-based competitive balance measure: A defense. *Journal of Sports Economics*, *4*(1), 74-80.

El-Hodiri, M., & Quirk J. (1971). The economic theory of a professional sports league. *Journal of Political Economy*, 79, 1302-1319.

Fenn, A. J., von Allmen, P., Brook, S., & Preissing, T. J. (2005). The influence of structural changes and international players on competitive balance in the NHL. *Atlantic Economic Journal*, *33*(2), 215-224.

Fizel, J. (1997). Free agency and competitive balance. *Stee-rike four*, 61-72.

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

Forrest, D., Beaumont, J., Goddard, J., & Simmons, R. (2005). Home advantage and the debate about competitive balance in professional sports leagues. *Journal of Sports Sciences*, *23*(4), 439-445.

Forrest, D., Simmons, R., & Buraimo, B. (2005). Outcome uncertainty and the couch potato audience. *Scottish Journal of Political Economy*, *52*(4), 641-661

Fort, R. (2003). Thinking (some more) about competitive balance. Journal of Sports Economics, 4(4), 280-283.

Fort, R. (2006). Competitive balance in North American professional sports. *Handbook of sports economics research*, 190-206.

Fort, R. & Lee, Y. H. (2006). Stationarity and MLB attendance analysis. *Journal of Sports Economics*, 7, 408-415.

Fort, R., & Maxcy, J. (2003). Comment: Competitive balance in sports leagues: An introduction. *Journal of Sports Economics*, 4, 154-160.

Fort, R., & Quirk, J. (1995). Cross-subsidization, incentives, and outcomes in professional team sports leagues. *Journal of Economic Literature*, 23, 1265-1299.

Fort, R., & Quirk, J. (2004). Owner objectives and competitive balance. *Journal of Sports Economics*, *5*(1), 20-32.

Grier, K. B., & Tollison, R. D. (1994). The rookie draft and competitive balance: The case of professional football. *Journal of Economic Behavior & Organization*, *25*(2), 293-298.

Grossmann, M., Dietl, H., & Lang, M. (2010). Revenue sharing and competitive balance in a dynamic contest model. *Review of industrial organization*, *36*(1), 17-36.

Gustafson, E., & Hadley, L. (2007). Revenue, population, and competitive balance in major league baseball. *Contemporary Economic Policy*, *25*(2), 250-261.

Hadley, L., Cieka, J., & Krautmann, A. (2005). Competitive balance in the aftermath of the 1994 players' strike. *Journal of Sports Economics*, 6, 379-389.

Haugen, K. K. (2008). Point score systems and competitive imbalance in professional soccer. *Journal of Sports Economics*, *9*(2), 191-210.

Horowitz, I. (1997). The increasing competitive balance in Major League Baseball. *Review of Industrial Organization*, *12*(3), 373-387.

Humphreys, B. (2002). Alternative measures of competitive balance in sports leagues. *Journal of Sports Economics*, 3, 133-148.

Humphreys, B. (2003a). Comments on "Thinking about competitive balance." *Journal of Sports Economics*, 4(4), 284-287.

Humphreys, B. R. (2003b). The ANOVA-based competitive balance measure: A reply. *Journal of Sports Economics*, *4*(1), 81-82.

Jennett, N. (1984). Attendances, uncertainty of outcome and policy in Scottish league football. *Scottish Journal of Political Economy*, 31, 176-188.

Kahane, L. (2003). Comments on “Thinking about competitive balance.” *Journal of Sports Economics*, 4(4), 288-291.

Kesenne, S. (2000a). The impact of salary caps in professional team sports. *Scottish Journal of Political Economy*, *47*(4), 422-430.

Késenne, S. (2000b). Revenue sharing and competitive balance in professional team sports. *Journal of Sports Economics*, *1*(1), 56-65.

Kesenne, S. (2004). Competitive balance and revenue sharing when rich clubs have poor teams. *Journal of Sports Economics*, *5*(2), 206-212.

Késenne, S. (2005). Revenue Sharing and Competitive Balance Does the Invariance Proposition Hold?. *Journal of Sports Economics*, *6*(1), 98-106.

King, N., Owen, P. D., & Audas, R. (2012). Playoff Uncertainty, Match Uncertainty and Attendance at Australian National Rugby League Matches..*Economic Record*, 88, 262-277.

Knowles, G., Sherony, K., Haupert, M. (1992). The demand for major league baseball: A test of the uncertainty of outcome hypothesis. *The American Economist*, 36(2), 72-80.

Krautmann, A, & Hadley, L. (2006). Dynasties versus pennant races: Competitive balance in major league baseball. *Managerial Decision and Economics*, 27, 287-292.

Krautmann, A., Lee, Y., & Quinn, K. (2011). Playoff uncertainty and pennant races. *Journal of Sports Economics*, 12, 495-514.

Larsen, A., Fenn, A., & Spenner, E. (2006). The impact of free agency and the salary cap on competitive balance in the National Football League. *Journal of Sports Economics*, 7, 374-390.

Lee, T. (2010). Competitive balance in the National Football League after the 1993 collective bargaining agreement. *Journal of Sports Economics*, 11(1), 77-88.

Lee, Y. H. (2004). Competitive balance and attendance in Japanese, Korean and U.S. professional baseball leagues. In R. Fort and J. Fizel (Eds.), *International Sports Economics Comparisons* (pp. 281-291). Westport, CT: Praeger.

Lee, Y. H. (2009). The impact of postseason restructuring on the competitive balance and fan demand in Major League Baseball. *Journal of Sports Economics*, 10, 219-235.

Lee, Y. H. & Fort, R. (2008). Attendance and the uncertainty-of-outcome hypothesis in baseball. *Review of Industrial Organization*, 33, 281-295.

Lee, Y. H., & Fort, R. (2012). Competitive Balance: Time Series Lessons from the English Premier League. *Scottish Journal of Political Economy*, *59*(3), 266-282.

Lemke, R. J., Leonard, M., & Tlhokwane, K. (2010). Estimating attendance at Major League Baseball games for the 2007 season. *Journal of Sports Economics*, *11*(3), 316-348.

Lenten, L. J. (2009a). Towards a New Dynamic Measure of Competitive Balance: A Study Applied to Australia's Two Major Professional 'Football' Leagues. *Economic Analysis and Policy*, *39*(3), 407.

Lenten, L. J. (2009b). Unobserved Components in Competitive Balance and Match Attendances in the Australian Football League, 1945–2005: Where is all the Action Happening? *Economic Record*, *85*(269), 181-196.

Levin, M. A., & McDonald, R. E. (2009). The value of competition: competitive balance as a predictor of attendance in spectator sports. *International Journal of Sports Marketing and Sponsorship*, *11*(1), 7-24.

Levin, R., Mitchell, G., Volcker, P., & Will, G. (2000). *The report of the independent members of the Commissioner's Blue Ribbon Panel on baseball economics*. New York: Major League Baseball. Retrieved from http://www.mlb.com/mlb/downloads/blue_ribbon.pdf

Lewis, M. (2008). Individual team incentives and managing competitive balance in sports leagues: an empirical analysis of major league baseball. *Journal of Marketing Research*, *45*(5), 535-549.

Long, J. G. (2005). Full count: The real cost of public funding for major league sports facilities. *Journal of Sports Economics*, *6*(2), 119-143.

Longley, N. & Lacey, N. J. (2012). The "second" season: The effects of playoff tournaments on competitive balance outcomes in the NHL and NBA. *Journal of Sports Economics*, 13, 471-493.

Manasis, V., Avgerinou, V., Ntzoufras, I., & Reade, J. J. (2011). Measurement of competitive balance in professional team sports using the Normalized Concentration Ratio. *Economics Bulletin*, *31*(3), 2529-2540.

Mastromarco, C., & Runkel, M. (2009). Rule changes and competitive balance in Formula One motor racing. *Applied Economics*, *41*(23), 3003-3014.

Maxcy, J., & Mondello, M. (2006). The impact of free agency on competitive balance in North American professional team sports leagues. *Journal of Sport Management*, *20*(3), 345-365.

Meehan, Jr. J., Nelson, R., & Richardson, T. (2007). Competitive balance and game attendance in Major League Baseball. *Journal of Sports Economics*, 8, 563-580.

Miller, P. A. (2007). Revenue Sharing in Sports Leagues The Effects on Talent Distribution and Competitive Balance. *Journal of Sports Economics*, *8*(1), 62-82.

Mizak, D., Stair, A., & Rossi, A. (2005). Assessing alternative competitive balance measures for sports leagues: a theoretical examination of standard deviations, Gini coefficients, the index of dissimilarity. *Economics Bulletin*, *12*(5), 1-11.

Mizak, D., Neral, J., & Stair, A. (2007). The adjusted churn: an index of competitive balance for sports leagues based on changes in team standings over time. *Economics Bulletin*, 26, 1-7.

Neale, W. (1964). The peculiar economics of professional sports. *The Quarterly Journal of Economics*, 78(1), 1-14.

O'Reilly, N., Kaplan, A., Rahinel, R., & Nadeau, J. (2008). "If You Can't Win, Why Should I Buy a Ticket?": Hope, Fan Welfare, and Competitive Balance. *International Journal of Sport Finance*, *3*(2), 106-118.

Owen, P. D. (2010). Limitations of the relative standard deviation of win percentages for measuring competitive balance in sports leagues. *Economics Letters*, *109*(1), 38-41.

Owen, P. D. (2012). Measuring Parity in Sports Leagues with Draws Further Comments. *Journal of Sports Economics*, *13*(1), 85-95.

Owen, P., & Weatherston, C. (2004). Uncertainty of outcome and super 12 rugby union attendance: Application of a general-to-specific modeling strategy. *Journal of Sports Economics*, 5, 347-370.

Owen, P. D., Ryan, M., & Weatherston, C. R. (2007). Measuring competitive balance in professional team sports using the Herfindahl-Hirschman Index. *Review of Industrial Organization*, *31*(4), 289-302.

Paul, R., & Weinbach, A. (2007). The uncertainty of outcome and scoring effects on the Nielsen ratings for Monday night football. *Journal of Economics and Business*, 59, 199-211.

Paul, R., Wachsman, Y., & Weinbach, A. (2011) The role of uncertainty of outcome and scoring in the determination of fan satisfaction in the NFL. *Journal of Sports Economics*, 12(2), 213-221.

Pawlowski, T., & Anders, C. (2012). Stadium attendance in German professional football–the (un) importance of uncertainty of outcome reconsidered. *Applied Economics Letters*, *19*(16), 1553-1556.

Pawlowski, T., Breuer, C., & Hovemann, A. (2010). Top clubs' performance and the competitive situation in European domestic football competitions. *Journal of sports economics*, *11*(2), 186-202.

Peel, D., & Thomas, D. (1988). Outcome uncertainty and the demand for football: an analysis of match attendance in the English football league. *Scottish Journal of Political Economy*, 35(3), 242-249.

Peel, D., & Thomas, D. (1992). The demand for football: Some evidence on outcome uncertainty. *Empirical Economics*, 17, 323-331.

Peel, D., & Thomas, D. (1997). Handicaps, outcome uncertainty and attendance demand. *Applied Economics Letters*, *4*(9), 567-570.

Peeters, T. (2011). Broadcast rights and competitive balance in European soccer. *International Journal of Sport Finance*, *6*(1), 23-39.

Quirk, J., & Fort R. D. (1992). *Pay dirt: The business of professional team sports*. Princeton, NJ: Princeton University Press.

Richardson, D. H. (2000). Pay, performance, and competitive balance in the National Hockey League. *Eastern Economic Journal*, *26*(4), 393-417.

Rogers, P. (2001). Baseball's flaw: lack of competitive balance. *Chicago Tribune*. Retrieved from http://articles.chicagotribune.com/2001-12-18/sports/0112180248_1_competitive-balance-major-league-baseball-payroll

Rottenberg, S. (1956). The baseball players' labor market. *The Journal of Political Economy*, 64, 242-258.

Russo, R. (2012). College football playoffs: BCS to be replaced by four-team playoff in 2014. *The Huffington Post*. Retrieved from http://www.huffingtonpost.com/2012/06/26/college-football-playoffs_n_1628960.html

Sanderson, A. (2002). The many dimensions of competitive balance. *Journal of Sports Economics*, 3, 204-228.

Sanderson, A., & Siegfried, J. (2003). Thinking about competitive balance. *Journal of Sports Economics*, 4, 255-279.

Schmidt, M. B., & Berri, D. J. (2001). Competitive balance and attendance: The case of major league baseball. *Journal of Sport Economics*, 2, 145-167.

Schmidt, M. B., & Berri, D. J. (2002). Competitive balance and market size in major league baseball: A response to Baseball's Blue Ribbon Panel. *Review of Industrial Organization*, *21*(1), 41-54.

Schmidt, M. B., & Berri, D. J. (2003). On the evolution of competitive balance: The impact of an increasing global search. *Economic Inquiry*, *41*(4), 692-704.

Schmidt, M. B., & Berri, D. J. (2004). The impact of labor strikes on consumer demand: An application to professional sports. *American Economic Review*, 344-357.

Scully, G. (1989). *The Business of Major League Baseball*. Chicago: University of Chicago Press.

Soebbing, B. P. (2007). Competitive balance and attendance in major league baseball: An empirical test of the uncertainty of outcome hypothesis. *International Journal of Sport Finance*, *3*(2), 119-126.

Sutter, D., & Winkler, S. (2003). NCAA scholarship limits and competitive balance in college football. *Journal of Sports Economics*, *4*(1), 3-18.

Szymanski, S. (2001). Income inequality, competitive balance and the attractiveness of team sports: Some evidence and a natural experiment from English soccer. *The Economic Journal*, *111*(469), 69-84.

Szymanski, S. (2003). The economic design of sporting contests. *Journal of Economic Literature*, 41, 1137-1187.

Szymanski, S. (2007). The champions league and the Coase theorem. *Scottish Journal of Political Economy*, *54*(3), 355-373.

Szymanski, S., & Kesenne, S. (2004). Competitive balance and gate revenue sharing in team sports. *The Journal of Industrial Economics*, *52*(1), 165-177.

Tainsky, S., & Winfree, J. A. (2010). Short-run demand and uncertainty of outcome in Major League Baseball. *Review of Industrial Organization*, *37*(3), 197-214.

Utt, J., & Fort, R. (2002). Pitfalls to measuring competitive balance with Gini coefficients. *Journal of Sports Economics*, *3*(4), 367-373.

Vrooman, J. (1995). A general theory of professional sports leagues. *Southern Economic Journal*, 971-990.

Vrooman, J. (2009). Theory of the perfect game: Competitive balance in monopoly sports leagues. *Review of Industrial Organization*, *34*(1), 5-44.

Zimbalist, A. (2002). Competitive balance in sports leagues: An introduction. *Journal of Sports Economics*, 3, 111-121.

Zimbalist, A. (2003). Competitive Balance Conundrums Response to Fort and Maxcy's Comment. *Journal of Sports Economics*, *4*(2), 161-163.