Winning the Lottery: Measuring the Effect of Changes in the NBA Draft Structure on Competitive Balance and Attendance

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Abstract

Professional sports are often thought of as a game, but in reality they are also a business. Like most other business, professional sports leagues are trying to maximize their profits. While there are many components that affect a league's profitability, one aspect is the competitive balance of the league. Studies have generally shown that a greater level of parity in a sports league generates greater attendance and therefore greater league profits. Even as this is the case, professional leagues have a very difficult time creating a more competitive atmosphere. Some teams will inherently have more economic resources at their disposal, either because of a wealthy owner, a strong location, or simply a long-standing history that has spawned a large fan base. Nonetheless, leagues utilize any means they can of affecting a more balanced environment. But how effective are their efforts?

In this paper, I analyze the effect that rule changes in the draft procedure have had on competitive balance in the National Basketball Association (NBA). To do this, I look at the changes in the NBA draft, including the adoption of the draft lottery and the weighted draft lottery, and look at the impact those changes had on the competitive balance in the league. From there, I will look at the effect that these changes had on overall league attendance for lottery teams as opposed to non lottery teams. I find that some models show that the introduction of the lottery led to a significant decrease in competitive balance and most models show that the change to weighted lottery led to a significant decrease in balance. Attendance does appear to have been affected differently for teams participating in the lottery versus those not in the lottery.

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I. Introduction

Professional sports are often thought of as a game, but in reality they are also a business. Like most other businesses, professional sports teams are trying to maximize their profits. While there are many components that affect the profitability of teams in a league, one aspect is the competitive balance of the league. Studies have generally shown that a greater level of parity in a sports league generates greater attendance and therefore greater league profits. Even as this is the case, professional leagues have a very difficult time creating a more competitive atmosphere. Some teams will inherently have more economic resources at their disposal, either because of a wealthy owner, a strong location, or a long-standing history that has spawned a large fan base. Nonetheless, leagues utilize any means they can of effecting a more balanced environment. But how effective are their efforts?

In this paper, I will analyze the effect that rule changes in the draft procedure have had on competitive balance in the National Basketball Association (NBA). To do this, I will look at the shortening of the draft, the adoption of the draft lottery and the weighted draft lottery, and the prohibition of high school students going straight to the NBA. I will then look at the impact those changes had on the competitive balance in the league and, from there, the direct effect of changes in draft structure on league attendance.

One argument leagues make for a draft is that the draft can improve competitive balance. Whether current drafts actually improve parity is an open question. Give the small roster size, higher draft picks have the potential to have a large effect on the future of a team in the NBA. The Cleveland Cavaliers instantly went from 17-65 prior to drafting LeBron James to a number two seed in the Eastern Conference in just his third year and an appearance in the NBA finals in his fourth season. This impact is less likely in a sport like baseball, where one draft pick is much less likely to change the path of the franchise.

Equally important as the effect of a draft on competitive balance is the impact of the draft on league attendance, as a major piece of league revenue comes from ticket purchases. Consequently, with greater league attendance and correspondingly greater ticket purchases, league revenue will increase. With professional sports leagues being first and foremost a business, it is important to look at whether the past and current draft systems are beneficial to increasing attendance either independently or through their impact on competitive balance.

The NBA is a particular interesting case to look at in terms of competitive balance. Every NBA team has made the playoffs at least once since 2004, making the Minnesota Timberwolves seven year drought the longest in the league. This makes the NBA appear more competitive than other professional leagues such as the MLB, where the Pittsburgh Pirates are currently in the midst of a stretch of 19 consecutive losing seasons. But playoff presence as a measure of competitive balance can be deceptive, since over half the teams in the NBA make the playoffs each year. In fact, recent studies have shown that the NBA has both historically and in recent years been the least competitive professional league.

The research in this paper takes data from the NBA from 1980 to the present. After defining measures of competitive balance, data from each team are compiled to create annual measures. Data on league attendance for each season are also used to find the movement of attendance over time. These data are supplemented by census data that will allow me to account for other determinants of league attendance.

The models show that changes to the NBA draft structure did in fact affect the competitive balance of the league. Models differ on the significance of the introduction of the lottery, but some show that it significantly decreased competitive balance league-wide. The models agree that changing to a weighted lottery system significantly decreased competitive balance. The changes to the lottery did not appear to have a large affect on the attendance of teams in the lottery as compared to teams not participating in the lottery.

The structure of this paper is as follows: In Section II, I will review literature relevant to the subjects of competitive balance and the determinants of attendance. This section will be divided into three parts. I will first look at papers that have examined means of measuring competitive balance. I will then look at literature surrounding the effects of league changes on competitive balance. Lastly, I will review the literature that discusses the determinants of attendance in professional sports leagues, as this will affect the procedure by which I determine the effect of the draft on league attendance. In Section III, I will give a brief history of the NBA draft and how it has changed. In Section IV, I will discuss the data that will be used in the calculations and the sources of that data. I will also present the measurements that I will use to calculate competitive balance. In Section V, I present the models I will use for determining the effect of the draft on competitive balance and ultimately its effect on attendance. In Section VI, I will then analyze the findings of the models in the previous section. Lastly, Section VII will conclude the paper and summarize the results.

II. Literature Review

Though there has been no literature on the effect of the NBA draft structure on competitive balance, there has been extensive research about competitive balance in sports leagues. The literature pertinent to this paper can be divided into three categories: measuring competitive balance, factors affecting competitive balance, and determinants of attendance.

Measures of Competitive Balance

Two different ways of measuring competitive balance have been used extensively. The first focuses on team winning percentage across seasons, taking each team's winning percentage in a number of seasons and looking at the standard deviation from the mean winning percentage for that team. This is then applied to all teams in the league to look at how dispersed each team's winning percentage has been over a given time period. The second measurement centers around league winning percentage, measuring the competitive balance in one season and comparing that figure across seasons. This takes each team's winning percentage during a season and looks at the standard deviation of that winning percentage from an "idealized" mean of .500, which would be the case if each team had an identical record (the same number of wins and losses). Each of these measures taken alone is not sufficient to measure competitive balance, as neither captures variations in relative rankings of one team to another.

Noll (1988) and Scully (1989) develop a common competitive balance measurement using the standard deviation of winning percentages within a league to measure that league's competitive balance. Scully claims that the natural way to measure competitive balance is to compare the actual performance of teams in a league to that of an ideal league where all teams were perfectly equal. He finds that, for major league baseball, two-thirds of teams should statistically lie between the win percentages of .342 and .658 (1.58 above and below the mean win percentage). He also finds that win percentage dispersion has decreased over time, attributing this to factors such as more teams within the league and more games played each season.

Quirk and Fort (1992) take this approach to measure competitive balance in baseball and football. They claim that the trend towards a more competitive baseball league is due not only to the reasons of Scully but also to moves by teams to more profitable markets, the introduction of a reverse-order draft, and the disappearance of the sales of star players. Quirk and Fort also use a measure of the dispersion of championships within a league to determine competitive balance. They use the Lorenz Curve as a measure of inequality in the winning of league championships, claiming that over a sufficiently long period of time, championships should equalize among teams within the league. Finally, Quirk and Fort suggest a lifetime team win percentage measure of competitive balance. This combines the standard deviation method of comparing winning percentages with the added value of spanning a longer time period (taken into account by the dispersion of championships method).

Humphreys (2002) claims that while the standard deviation measure of competitive balance used by Scully is sensible for one season, it is not able to capture changes in relative team standings from one year to the next. He demonstrates this with two leagues that would appear to have the same level of balance over a five year period, but in one league the standings remained the same each year and in the other the teams changed their ranking in the standings every season. To combat this problem, Humphreys proposes an alternative measure of competitive balance called the Competitive Balance Ratio (CBR). The CBR places the standard deviation of each team's winning percentage across seasons in the numerator and puts the standard deviation of winning percentage in each season across all teams in the denominator, therefore "scal[ing] the average time variation in won-loss percentage for teams in the league by the average variation in won-loss percentage across seasons" (137). A higher CBR indicates a more competitive league.

Lee (2010) uses a very different approach to measure competitive balance. Lee theorizes that over a sufficiently large sample of seasons, every team should be expected to finish in first place, last place, and any other positions in a perfectly balanced league. Therefore, an immediate method of measuring competitive balance is to look at the effect of the previous year's winning percentage on the current year winning percentage for each team. The smaller the effect of the previous year's winning percentage, the greater is the balance within the league.

Determinants of Competitive Balance

Using the measurements discussed above, as well as others such as the Gini coefficient and the Herfindahl-Hirschman Index, much literature has focused on factors affecting the competitive balance within a league. This literature is very diverse in not only the different factors it considers, but also the leagues on which it focuses.

Kesenne (2000) addresses the issue of revenue sharing and competitive balance in sports leagues, which has been looked at extensively. He points out that, as shown by Rottenberg (1956), Quirk and El-Hodiri (1974) and many others since, revenue sharing does not affect the competitive balance within a league with a fixed labor supply if teams are strictly profit-maximizing, because lower spending team's will keep the profits earned from those that spend more. He then showed that, assuming the impact of team quality on team revenue is different between teams in a league, "if the larger drawing potential of a franchise also implies a larger impact of the quality factor, a decrease in the home team revenue share leads to a more competitive balance."

The degree of revenue sharing must be taken into account when measuring the effect on balance, however, as professional leagues vary greatly in the extent of revenue sharing. While the NBA revenue sharing system only calls for dividing the national television revenues and luxury tax proceeds, the NFL and MLB both have larger revenue sharing policies in place, including the division of local revenues to redistribute revenue to small-market teams.

During labor negotiations, arguments are consistently made that comprehensive free agency leads to a more balanced league. Larsen, Fenn, & Spenner (2006) look at the effect of free agency, as well as the salary cap, stadium construction, and player strikes on competitive balance in the National Football League (NFL). Following a model developed by Depken (1999), Larsen, Fenn, and Spenner use a form of the Herfindahl-Hirschman Index, but with adjustments to account for league expansion. They add variables to control for other league changes, including schedule length, number of playoff spots, team relocations, new stadium construction, and various league strikes. They also add a variable to indicate team talent level, as Depken showed that competitive balance is affected by the dispersion of talent. They find that the combined introduction of free agency and a salary cap increased balance in the NFL, differing from Depken's findings that free agency had no affect on the National League and minimally increased balance in the American League. In addition, Larsen, Fenn, and Spenner find that more highly concentrated talent decreases balance, as do a longer season, an expanded number of playoff spots, and the creation of new stadiums. They also find that league expansion and team relocation do not have significant effects of league balance.

Berri et al. (2005) use the measurement developed by Noll and Scully to compare the average competitive balance for many seasons across different sports leagues. Their findings are that soccer and American football leagues typically are the most competitive, with hockey, baseball, and basketball finishing in that order of competitiveness. Basketball leagues finished significantly less competitive than the other sports, and Berri et al. showed that the NBA was the only major sports league to become less competitive in the 1990s. They find that the NBA's competitive balance was fairly consistent before the 1990s, though it was the least balanced of all sports leagues, but then became less balanced in the 1990s. They speculate that the reason that the NBA is so imbalanced is because leagues become more balanced when drawing from a larger population, and with NBA players being so tall, the NBA has a much smaller population from which to draw. They then create a measure of player performance and find that taller players (which they define as eighty-two inches or greater) do in fact have a greater standard deviation in performance level than do shorter players, supporting their original hypothesis.

Individual players have the ability to improve a team more in basketball than in other professional sports, giving motivation to losing teams to try for the highest draft pick. Recently, Berri and Schmidt (2010) looked at the benefits for bottom-feeder NBA teams to lose intentionally in order to secure a number one draft pick. This "losing to win" scheme is the reason that the NBA adopted a lottery style draft as opposed to a traditional worst-to-first order. In their research, Berri and Schmidt looked at a measure of wins produced in the first five NBA seasons for the number one and number two picks in each draft from 1977-2004. They found that number one picks produced an average of 46.7 wins and number two picks produced an average of 27.6 wins. They also looked at the monetary implications of having the first pick as opposed to the second or third. They found that from 1985-2006, having a number one draft selection earns over $2 million more in gate revenue than having the second selection (over the first two years of that draft pick's career). The number two choice then generated almost $1.5 million more in gate revenue than the third pick. Therefore, there are both monetary and success reasons for a struggling team to lose on purpose in order to get the first draft choice, verifying the NBA's decision to move to a weighted draft lottery and lessen the urge to lose intentionally.

Determinants of Attendance

Before analyzing the effect of the lottery on team attendance, it is important to look at what other factors affect league attendance. There is extensive literature on this topic, as attendance is what earns team revenue and ultimately drives the league.

Leadley and Zygmont (2005) look at the presence of a "honeymoon effect" in the NBA from 1971-2000. The honeymoon effect is the relationship between spectator attendance and the age of the arena in which a team plays. Leadley and Zygmont use average attendance per home game and general admission ticket price as their dependent variables. They included independent variables for real income and population on a city wide basis as well as variables to capture absolute and relative team quality. Because so many NBA games sell out, they added a dummy variable for if the stadium was 95% full or more as a measure of whether the demand for tickets was constrained by stadium capacity. They also note that prices are set at the beginning of the season based on the team's performance in the previous season. Therefore, they include lagged variables for the team's previous year winning percentage and games behind. Finally, they have a dummy variable for each of the first fifteen years of a team's operation in that city and each of the first fifteen years after a new stadium is constructed. Ultimately, Leadley and Zygmont find that the honeymoon effect does exist in the NBA. Attendance is increased the first four years after a new arena is constructed, after which the honeymoon effect steadily declines until it totally disappears completely after year ten. They find that the presence of a new team is not statistically significant for any of the fifteen years tested, likely because a city that did not already have a team is a smaller market with fewer fans.

Fedderson and Maennig (2009) look at the difference in attendance for a monofunctional arena versus a multifunctional arena in the German professional soccer league. They set up a model for stadium attendance to test for this effect, including variables for team success (measured as the final position in the league that the team finished in the season in question) and playoff success (taking a value of 0, .25, .5, .75, or 1 depending on how far the team went in the playoffs). Another variable looks at the market for spectators, as measured by the number of league rivals for each team within a 100-km radius of the team's hometown, as well as a variable for the population of the team's city and income. They include a variable for the percentage of home games played during the week because attendance is typically greater on weekends.

To isolate the effect of a new arena on attendance, Fedderson and Maennig must include a variable for each team's stadium capacity. As they point out, for a team with a regularly sold out stadium, it is difficult to tell whether an increase in attendance is simply due to a new stadium or to a larger stadium capacity. To take capacity into account, they use a variable that assumes the value of the percentage capacity change for teams that exhibited an average capacity utilization of over 90% previous three seasons leading up to the opening of a new stadium, with the variable taking on a value of 0 if the capacity utilization was below 90%.

Fedderson and Maennig find that an additional team in the club's home market reduces attendance by approximately 390 patrons, and finishing in one position lower in the standings reduces attendance by about 440 patrons. They also find that the variable isolating an increased stadium capacity is positive and significant, meaning that there had been un-met demand prior to the stadium expansion. Finally, they find that a newly built stadium leads to an increase of about 8.5% in attendance, and that a strictly-soccer arena leads to a 10.7% leap in attendance over a multifunctional arena.

Berri, Schmidt, and Brook (2004) look at the impact of star power on gate revenues in the NBA from the 1992-1993 season through the 1995-1996 season. To measure star power, they looked at the number of all-star votes received by players, as fans vote for the all-star team and the top vote-getters are therefore perceived by the fans as stars. They then created a variable for the number of all-star votes a team received and a dummy-variable for the presence of the number one vote-getter in any year. They used franchise characteristic variables in the model including team wins, stadium age, stadium capacity, a weighted measure of championship wins, and whether or not the team was an expansion team. Since so many stadiums were sold out in those seasons, they used gate revenue as the dependent variable as opposed to attendance to capture an increase in the price level for team's whose demand exceeded the supply of seats. They also included a measure of roster stability by looking at "the minutes played by returning players over both the current and prior seasons" (37).

For market characteristics, they use a measure of league competitive balance, the number of competing sports teams from other leagues in the same city, population, and per-capita income. In addition, they create a variable for a ratio of the percentage of minutes played by white players on the team to the percentage of the city's population that is white. The white population variable and per-capita income were not found to be significant.

Berri, Schmidt, and Brook found that wins and stadium capacity had the largest effect on gate revenues. Neither the dummy variables for the presence of a top vote-getter nor the all-star votes variable had a significant effect on gate revenues. Interestingly, their results also show that, contrary to their findings in other research, competitive balance does not have an effect on gate revenue. They attributed this to the fact that their model included a very short time period.

Competitive Balance and Attendance

The link between competitive balance and attendance has been looked at in many studies. Peel and Thomas (1988) study the effect of uncertainty on attendance in an English football league. They use pregame odds data as a measure of uncertainty, and find that match attendance is maximized when the home team has a 60% chance of winning the game. Rascher (1999) looks at the 1996 baseball season and finds that attendance is maximized when the home team has a 66% chance of winning. Under either circumstance, however, when the home team's win probability gets too high, the game attendance decreases.

Schmidt and Berri (2001) look at the relation between competitive balance and attendance in Major League Baseball using the Gini index to measure balance. Their measure of balance indicates that the MLB became more competitive over time and particularly in the 1980s and 1990s, which they stipulated was caused by the advent of free agency and the reverse-order draft. Schmidt and Berri wanted to capture not only the effect of competitive balance within each season but also whether persistent imbalance led to further declines in attendance. They looked at this effect by not only using individual season measures for balance but also 3-year and 5-year averages. Using a time-series model, their results established a strong connection between balance and attendance, as all Gini measures for both the American and National Leagues were negative and statistically significant at the 1% level. When using panel data, they also found that the coefficient for balance was positive and significant, indicating that fans do have a preference for parity. The 3-year and 5-year coefficients remained significantly negative, showing that persistent balance does drag down attendance.

III. NBA Draft History

The NBA draft began in 1947 with what resembled a "worst-to-first" format that is common in professional sports today, whereby the team with the worst record gets the first pick, the second worst record receives the second pick, and so forth. The draft was not strictly a worst-to-first format because teams could forfeit their draft choice to use a territorial pick and select a local player. In 1965, the NBA got rid of territorial picks and changed the draft to include a coin-flip between the worst teams in each conference for the first selection, and a worst-to-first format for the remainder of the draft. The reason the draft was structured this way was to allow poor teams to improve by having the opportunity to select the best players in the draft with the top picks. The problem with this draft format, however, is that it perpetuates "tanking," or losing intentionally to try to receive a higher draft pick. Teams that know they will not make the playoffs have no incentive to try their hardest to win games, which means they could sit their best players. This hurts attendance, as fans do not want to pay to watch players they have never heard of.

In an attempt to prevent tanking, the NBA changed to a lottery format before the 1985 draft. This new format gave all teams that did not make the playoffs an equal shot at the first pick or any pick thereafter. This gives teams no incentive to tank, but also could mean that teams that barely miss the playoffs get much higher picks than those that finish in last place.

In 1989, the NBA once again changed the draft to a weighted lottery format. This change keeps the lottery format, but weights it such that the teams finishing lower in the standings have a greater chance at the top pick. While the exact odds have changed slightly over the years, currently the last placed team has a 25% chance at the top pick, the team with the second worst record has a 19.9% chance at the top pick, and the percentages continue to decrease until the team that misses the playoffs with the best record has a minuscule chance.

IV. Data Description

Data were collected for each NBA team in each season from 1981-2010, making for 818 maximum total observations. Multiple sources were used to accumulate data for different variables in the model. The data can be broken down into three different groups: team-related data, stadium-related data, and population-related data.

Team-related data were collected for each season from DatabaseBasketball.com. These data include team wins and losses, games behind the first place team in the division, points for, points against, point differential, number of all-NBA players on each team, number of all-stars on each team, and playoff wins. Salary cap data for each year since the introduction of the cap were attained from ESPN.com.

Stadium-related data were collected from multiple sources. Team attendance and ticket prices were taken from Rodney Fort's Sports Business Data, though ticket price data were not available prior to the 1991 season. A comprehensive list of NBA stadiums was obtained from NBA Hoops Online, and stadium capacity numbers were verified from individual team and stadium websites.

Population, per-capita income, and unemployment data for metropolitan areas in which NBA teams in the United States were located were collected from the US Census Bureau and the Bureau of Labor Statistics. Demographic data for Canada were from Statistics Canada, statcan.com. Unemployment data were not available for all years in all metropolitan areas and was particularly difficult to find for Canadian cities.

Table 1 shows a complete list of variables included in both the competitive balance and attendance models, along with selected summary statistics.

TABLE 1: Competitive Balance and Attendance Model Variables

VARIABLE	DEFINITION	M	SD	MIN	MAX
CB	Standard deviation of wins throughout league	.158	.016	.115	.191
CBR	Measure of league and team competitive balance	.487	.790	.382	.974
PLAYOFF_WINS	Playoff wins as % of total wins needed to win title	.178	.273	0	1
PLAYOFF_ROUND	Round achieved in playoffs	1.09	1.23	0	4
PCT	Team winning percentage	.500	.156	.134	.878
NEW_ARENA	Binary for whether team's arena less than 5 years old	.122	.328	0	1

NBA_LOCKOUT	Binary for whether season shortened due to lockout	.035	.185	0	1
NHL_LOCKOUT	Binary for whether there was NHL lockout that season	.037	.188	0	1
SALARY_CAP	Binary for introduction of a salary cap	.916	.278	0	1
SAL_CAP_VAL	Value of the salary cap in that season	27.79	19.70	0	58.7
NEW_TEAM	Binary for whether team is in first 5 seasons in league	.048	.213	0	1
NEW_TEAMS	Number of new teams in the league in last year	.235	.615	0	2
PLAYOFF_TEAMS	Number of teams that make the playoffs	15.66	1.11	12	16
RELO	Binary for whether the team relocated in past 3 years	.034	.182	0	1
ALL_NBA	Number of first-team all-NBA players on the team	.183	.420	0	2
ALL_NBA_SD	Standard deviation of all-NBA players in the league	.425	.049	.379	.158
LOTTERY	Binary for the introduction of the draft lottery in 1985	.148	.355	0	1
WEIGHTED	Binary for the change to a weighted lottery in 1989	.74	.439	0	1
PDIFF	Team point differential	.009	386.6	-1246	1261
WCHAMPS	Weighted measure of team championships	3.623	6.447	0	20
ATTEND	Team attendance for the entire season	635523	150490	158887	1066505
CAPACITY	Stadium capacity	19327	6793	10333	80311
PCT_FULL	Percent of stadium that was full throughout the season	.839	.172	.12	1.0
PRICE	Weighted average ticket prices	41.39	14.27	15	93.25
LN_POP	Natural log of metro area population	15.04	.81	13.43	16.76
LN_INCOME	Natural log of metro area per-capita income	10.19	.39	9.18	11.04
LN_UNEMPLOY	Natural log on unemployment	1.63	.32	.76	2.75
OEFF	Measure of team offensive efficiency	103.85	4.175	89.8	124.5
DEFF	Measure of team defensive efficiency	103.43	3.626	89.3	112.5
LOT_TEAM	Binary for whether the teams took part in the lottery	.352	.478	0	1
PICK_DIFF	Difference between actual pick & worst-to-first pick	-.041	2.141	-11	6

V. Model

Competitive Balance Model Variables

I estimated several different models to measure the effect of changes in the draft structure on competitive balance. The first is based off of Humphreys' (2005) competitive balance ratio. In the competitive balance ratio, the numerator is a measure of within team variation in winning percentage across the entire dataset (1981-2010). It is calculated for each individual team as follows:

$$\sigma_{T,i} = \sqrt{\frac{\sum_t (WIN\_PCT_{i,t} - \overline{WIN\_PCT_i})^2}{T}}$$

In this equation, $WIN\_PCT_{i,t}$ is the winning percentage for team *t* in season *i*, which is compared to $\overline{WIN\_PCT_\iota}$, the team's mean winning percentage over the time span. This is calculated for each team in the league, and the average variation in team winning percentage is then formulated by dividing each team's $\sigma_{T,i}$ by the number of teams in the league.

The denominator in this model measures the variation of winning percentage of all teams in the league in each individual season from 1981-2010. It is calculated as follows:

$$\sigma_{N,t} = \sqrt{\frac{\sum_t (WIN\_PCT_{i,t} - 0.5)^2}{N}}$$

In the equation above, $WIN\_PCT_{i,t}$ is still the winning percentage for team *t* in season *i*. This is compared to a winning percentage of 0.5 because in a perfectly balanced league, each team would finish with the exact same record, having the same number of wins and losses.

In this paper, the CBR is used as the dependent variable in the third model. The first two models use the denominator from Humphreys' ratio, the standard deviation of wins within each season, which is a widely used measure of competitive balance to compare league-wide competitive balance on a year-by-year basis and see if there were any league wide changes after the league altered the draft structure.

The independent variables are listed in Table 1 above. The main variables of interest are *LOTTERY* and *WEIGHTED,* which measure the changes in competitive balance after those changes in the NBA draft structure. Other variables that can affect competitive balance are controlled for to limit omitted variable bias. These consist of any league-related or team-related changes that affect a team's winning percentage. League related changes include the introduction of a salary cap, a lockout shortened season, and the addition of new teams to the league. Team related changes that could affect competitive balance include the distribution of the best players within the league.

These first three models use league-wide measures of competitive balance, though the competitive balance ratio includes both league and team balance. These measures may fail to reveal important within-league variation in the impact of changes in the draft structure. For that reason, I also considered models that used team-level data to examine the impact of changes in the draft structure on parity. The first of these models regresses each team's winning percentage on their winning percentage from the previous season, as in Lee's paper, thus determining whether each individual team saw changes in its winning percentage over time or remained at a similar level across all seasons in the dataset. It is possible that balance would decrease since the institution of the lottery and weighted lottery, as bad teams do not always earn the top picks anymore. With this being the case, bad teams could remain bad for longer without improving due to getting the first pick.

To test for variation in individual team playoff success, two models that build on Lee's approach are used. These results are important because success in the league is not only measured by good records in the season but also by how far a team goes in the post-season. Limiting the models to only test for regular season competitive balance overlooks the importance of playoff success. The first of these models uses a dependent variable measuring team playoff wins each year, taking each team's playoff wins as a percentage of the number of playoff wins needed to win the championship. Therefore, the team that wins the championship will have a value of one for this variable, the team that loses the finals will have the second highest value, and so on. Teams that do not make the playoffs or get swept in the first round will have a value of 0 because they got no playoff wins. The second of these models uses a similar method, but measures the round that a team gets to instead of the number of playoff wins. This model assumes that a team is successful simply getting to the playoffs and then more successful as they advance each round, as opposed to being successful only if the team wins games in the round it reaches. A team is given a value of .25 for reaching the first round of the playoffs, .5 for reaching the second round, .75 for reaching the third round, and 1 for reaching the finals. These models look very similar to the previous ones that regress winning percentage on previous year's winning percentage, but instead regress playoff wins or round attained on those of the previous year for each team. The interaction variables measure changes in playoff success that can be attributed to the addition of the lottery or weighted lottery.

Attendance Model Variables

The second set of models I estimate are designed to measure the effect of league and team changes on attendance. The dependent variable is total team attendance in a season. One problem with measuring team attendance is that the maximum attendance is limited by stadium capacity. Many teams draw full stadiums and would likely be able to increase attendance if more seats were available. This is controlled for with a variable to control for the team's stadium capacity, and in one model a variable to capture what percentage of the stadium is full, as the demand for tickets will not be limited by the number of seats if the stadium is not close to full.

The main variable of focus in this model is *LOT_TEAM*, a dummy variable for whether a team was in the lottery. This measures whether the change in attendance after changes in the NBA draft structure is different for lottery versus non-lottery teams. Another variable of interest is *PICK_DIFF*, which measures the difference between where a team selected in the draft and where it would have selected had the worst-to-first draft format remained. This variable will obviously be zero for teams that did not take part in the lottery and can be positive or negative for lottery teams, depending on whether they received a higher selection than they would have in a worst-to-first format or a lower selection.

Many other variables affect attendance and therefore need to be taken into account. An increase in city population or per-capita income will likely increase the demand for basketball tickets, while demand is likely to be lower in metropolitan areas with higher unemployment. A team that has won more championships, particularly recent championships, or a team with more star players is also more likely to draw a larger crowd. In addition, a newly created team, a new stadium, or a newly relocated team frequently increases a team's attendance for a certain period of time afterword, found in previous studies to be four to five years. Other team-related variables such as wins, offensive and defensive efficiency, and point differential will also likely affect attendance, as a team with more wins will generally draw a greater attendance. Each team's top pick for each season is also controlled for so that the effects of being in the lottery can be isolated. Demand for tickets will most clearly be affected by the price of tickets at the stadium, as an increase in prices leads to a decrease in demand for all normal goods.

Model Specification – Competitive Balance

Because of the possibility of heteroskedasticity, I used robust standard errors when estimating the model and, where appropriate, clustered by team when calculating standard errors. The first model I estimated uses standard deviation of wins as the dependent variable:

(1) **MODEL 1**

$$CB_{it} = \beta_0 + \beta_1 NBA\_LOCKOUT_{it} + \beta_2 SALARY\_CAP_{it} + \beta_3 NEW\_TEAMS_{it} + \beta_4 P\_TEAMS_{it} + \beta_5 ALL\_NBA\_SD_{it} + \beta_6 LOTTERY_{it} + \beta_7 WEIGHTED_{it} + \varepsilon$$

Here, the dependent variables are league level variables which could affect the distribution of wins within the league. Therefore, variables related to balance within one individual season were not included. The NBA lockout, salary cap, and number of new teams within the league could all directly affect the spread of wins. In addition, the standard deviation of all-NBA players measures how dispersed the best players in the league are. Models 2 and 3 are very similar. The first uses the same dependent variable and all of the same explanatory variables but includes the value for the changes in salary cap each year as opposed to a dummy variable for whether or not there is a salary cap. The second uses the competitive balance ratio (CBR) as the dependent variable and includes the same explanatory variables as Model 1 above.

The fourth and fifth models looks at the effect of the previous year's winning percentage on the current year's winning percentage. This looks at the strength of the correlation between a team's success in one year and a team's success in the next year. A higher correlation would mean a less balanced league, as the same teams would be good each year. The first model is a fixed-effects model, whereas the next model uses fixed effects.

(2) **MODEL 4**

$$PCT_{it} = \beta_0 + \beta_1 PCT_{it-1} + \beta_2 LOTTERY\_INTERACTION_{it} + \beta_3 WEIGHTED\_INTERACTION_{it} + \varepsilon$$

This model looks at the impact of the lottery and the weighted lottery on competitive balance. To look at the direct effect of these changes, interaction variables are used between the addition of those draft formats and team winning percentage during the current year.

Finally, two fixed effects models are used to look at change in team playoff success over time. These models are very similar to the winning percentage model above, but measure playoff success instead of regular season success. The only difference between these two models is the dependant variable being either playoff round reached or playoff wins for each season. This takes a different approach to looking at variation in team success across seasons, assuming that the playoffs are the most important.

(3) MODEL 6

$$PLAYOFF\_ROUND_{it} = \beta_0 + \beta_1 PLAYOFF\_ROUND_{it-1} + \beta_2 LOT\_INTERACTION_{it} + \beta_3 WEIGHT\_INTERACTION_{it} + \varepsilon$$

Model Specification – Attendance

Eight attendance models are used to look at the effect of the lottery on attendance for teams in and teams not in the lottery. The first four do not include ticket price and unemployment, while the last four are the exact same but include ticket price and unemployment. Since not all data were available for these two variables, including them limits the number of observations. Being that unemployment was not found to be significant and regressions with unemployment produced very similar results to those without unemployment over the same number of observations in which unemployment data were available, excluding it should not largely affect the model. Ticket price would appear to have a great effect on attendance. However, ticket prices are correlated with other variables included in the model, such as the previous year's winning percentage and the metro area population. Therefore, even when ticket price is excluded, its effect on attendance should still be captured.

The first of the four different attendance models is a fixed effects regression with all variables specified linearly except for demographic level variables, capacity, and ticket price (in the models in which it is included). The second model is another fixed effects regression with the dependent variable also specified in logs. The explanatory variables are specified in logarithmic form in order to dampen the effect of outliers for those variables. For example, certain teams played at football stadiums with much greater capacities which could throw off the results of the model.

(4) MODEL 8

$$\begin{aligned} ATTEND_{it} = \; & \beta_0 + \beta_1 WIN\_PCT_{it} + \beta_2 WIN\_PCT_{it-1} + \beta_3 NEW\_ARENA_{it} \\ & + \beta_4 NBA\_LOCKOUT_{it} + \beta_5 NHL\_LOCKOUT_{it} + \beta_6 ALL\_STAR\_DIFF_{it} \\ & + \beta_7 NEW\_TEAM_{it} + \beta_8 RELO_{it} + \beta_9 ALL\_NBA_{it} \\ & + \beta_{10} OEFF_{it} + \beta_{11} DEFF_{it} + \beta_{12} PDIFF_{it} + \beta_{13} WCHAMPS_{it} + \beta_{14} CBR_{it} \\ & + \beta_{15} LN\_CAPACITY_{it} + \beta_{16} LN\_PRICE_{it} + \beta_{17} LN\_POP_{it} + \beta_{18} LN\_INCOME_{it} \\ & + \beta_{19} COMP\_BALANCE_{it} + \beta_{20} LOT\_TEAM_{it} + \beta_{21} PICK\_DIFF_{it} + \varepsilon \end{aligned}$$

Using fixed effects controls for the average differences across teams, and therefore leaves over just within-team affects. This controls for the possibility of omitted-variable bias in these regressions. Being that there are other unobservable characteristics that may be determinants of attendance and could be correlated with other variables already in the model, the use of fixed-effects dampens the impact of those unobserved characteristics. In addition, standard errors are again clustered. However, other possible problems do exist. One issue is that it is difficult to isolate the effect of the lottery through its impact on balance as opposed to the excitement effect. Attendance could be increasing not because a team's participation in the lottery is perceived to increase balance but rather because a higher pick causes fans to become more excited in the team. This was controlled for in part with the variable for the difference in actual and expected selection.

The final attendance regression uses a random effects model instead of the fixed effects model in the previous regressions. A random effects model assumes that the individual portion of the error term is not correlated with the explanatory variables. If this is the case, then using the random effects model will be more efficient than the previous fixed effects models. This proved to be false using a Sargan-Hansen test, which rejected that the fixed and random effects models were the same[1]. The random-effects model is still presented for comparison.

VI. Results

Competitive Balance Results

The regression analysis could logically lead to many different results, as instituting and changing the lottery could have contradictory effects. On one hand, a strict worst to first draft guarantees the last placed team the first pick in the draft, which would likely make the league more balanced than a lottery, in which teams with the worst records can get later picks. However, if the lottery achieved its goal and decreased tanking, bad teams would lose fewer games intentionally and the league would become more balanced.

Table 2 shows the results of the competitive balance models with the standard deviation of wins and the CBR as the dependent variables. The results with the standard deviation of wins as the dependent variable show that instituting the lottery increased the standard deviation of wins within the league, and therefore decreased within season competitive balance. The initial introduction of the lottery was statistically significant when including the value of changes in the salary cap and with a dummy for the introduction of the salary cap in the model. The modification of the lottery to weight it so that lower ranked teams have a higher chance of

[1] Sargan-Hansen test: chi2 = 236.569, 19 degrees of freedom

earning the first pick had the same effect. This change also decreased the competitive balance within the league and was also significant in both models.

Table 2: Within Season Competitive Balance

VARIABLES	(1) comp_balance	(2) comp_balance	(3) cbr
nba_lockout	-0.0069	-0.0033	0.0099
	(0.005)	(0.004)	(0.032)
sal_cap_value	-0.0004*		
	(0.000)		
new_teams	0.0036	0.0045	-0.0158*
	(0.003)	(0.003)	(0.009)
playoff_teams	-0.0013		
	(0.003)		
all_nba_sd	-0.1537**	-0.1218*	0.5132***
	(0.061)	(0.069)	(0.138)
weighted	0.0253***	0.0118***	-0.5672***
	(0.009)	(0.004)	(0.036)
lottery	0.0152***	0.0123**	-0.0643***
	(0.005)	(0.005)	(0.021)
salary_cap		-0.0045	0.0248
		(0.012)	(0.022)
Constant	0.2327***	0.2021***	-0.0635
	(0.051)	(0.032)	(0.068)
Observations	30	30	819
R-Squared	.5769	.6213	.6752

Robust standard errors in parenthesis
*** p<.01, ** p<.05, *p<.1

From this information, it appears that the introduction of the lottery decreased within-season parity in the NBA. This is likely the case because, between the two factors of decreased tanking and better teams sometimes receiving higher picks, the change in which teams earn the top picks had a larger effect. With all teams that make the lottery having an equal chance at the first pick, there was no reason for those teams to try to finish with a lower record. At the same time, bad teams might not get as high of a pick as they would have before the lottery, and therefore would not be able to improve as much. The latter had a larger effect and decreased competitive balance.

It is possible that there is simply a decreasing trend in competitive balance, and competitive balance was decreasing before the introduction of the lottery. This would mean that other unidentifiable factors were causing parity to decline. However, Berri, et. al (2005) showed that competitive balance was fairly stagnant up until the 1990s, when balance decreased throughout the league. This would indicate that competitive balance was not already on a downward trend before the introduction of the lottery.

The introduction of the weighted lottery would appear to solve the issue above, as worse teams receive a better chance of earning the first pick. Then why would the weighted lottery lead to decreased competitive balance? There are two main reasons. The first is that, while the weighted odds allow worse teams a better shot at the top pick, there is no guarantee. There were years under the regular lottery system, such as 1988, where the last placed Los Angeles Clippers received the first pick, and there have been years under the weighted system, such as 1993, where the Orlando Magic, with the eleventh worst record, received the first pick. Secondly, the weighted lottery incentivizes teams to tank even more than the strictly worst to first draft. With the weighted lottery, not only do the bottom two or three teams have reason to tank for the first pick, but all lottery teams benefit from tanking by increasing their odds of acquiring the top choice. This is consistent with recent findings by Walters and Williams (2012) that compared tanking before the introduction of the lottery in 1985 to after the weighted lottery began in 1989. They found increased tanking after 1989 than before 1985, which would likely lead to less parity after the introduction of the weighted lottery.

Of the other variables in the model, only the standard deviation of all-stars throughout the league was significant. The coefficient was negative, meaning that when all-stars are less spread out, competitive balance increases within the league. This is a surprising result, but could be possible because all-NBA players do not necessarily create better teams. In fact, it is possible that players that would be average on great teams become all-NBA players on poor teams because they need to carry the load. Chris Bosh is a prime example of this, as he remains an all-star on the Miami Heat but his statistics have dropped off since leaving the perennially losing Toronto Raptors. This result differs from that found by Larsen, Fenn, and Spenner (2006) in their study of the NFL, but this difference could simply be caused by differences between the NBA and NFL.

The third model in Table 2 using Humphrey's competitive balance ratio shows results very similar to those using the standard deviation of winning percentage. With the CBR as the dependent variable, both the change to lottery and the weighted lottery are found to have significantly decreased competitive balance, as was the case in the previous models. While the weighted lottery could have decreased balance for the reasons stated above, the introduction of the regular lottery could have decreased balance because bad teams were not able to improve as quickly being that the worst team and a team barely missing the playoffs had the same likelihood of earning the first draft choice. It makes sense that this model, while showing the same results as the first ones, would show an even greater impact of the introduction of the lottery because, unlike the first model, the competitive balance ratio takes into account team-related balance. Therefore while the standard deviation of wins during each season only accounts for the spread of wins that season and not whether the teams earning those wins are changing across seasons, the CBR captures when bad teams are staying bad and good teams are remaining good, a likely effect of granting higher picks to teams that did not finish at the bottom of the standings.

Adding additional teams to the league has a negative and significant coefficient in the CBR model and is not significant in the standard deviation model, meaning that more teams lead to less balance within a season. This is likely because the CBR accounts for teams' changes in wins across seasons. Therefore, while expansion teams generally are poor for at least a few years while they build talent, thus decreasing balance, these teams frequently increase their winning percentage greatly within their first few seasons, which the CBR takes into account in its team-related portion. An increase in the standard deviation of all-NBA players, or a greater concentration of all-NBA players on a small number of teams, has a positive and significant coefficient in the CBR model as well, which is consistent with the findings of the previous models and shows that the greater concentration of all-NBA players increases balance. Since the CBR takes into account team success over time, having a greater spread of all-NBA players could give more teams the opportunity to be successful, which could lead to changes in standings over time.

Table 3 has the regression of last year's winning percentage on this year's winning percentage for each team. The results did not show significant changes before and after the lottery. The previous year's winning percentage has a coefficient of .657, meaning that on average, one extra win the previous season will lead to .657 more wins in the current season. While the previous year's winning percentage has a very strong positive correlation with the current year's winning percentage, the interaction variables to test for whether that effect differed after the introduction of the lottery or the weighted lottery were not significant. The coefficient on the interaction variable for the introduction of the lottery indicates that one additional win the previous season would lead to .05 more wins in the current season after the introduction of the lottery than the increase in wins for this season would have been before the introduction of the lottery. The coefficient on the change to the weighted lottery is even lower; one additional win the previous season would lead to .007 more wins in the current season than the increase would have been before the weighted lottery. This means that, while the league became less balanced on a year-to-year basis, individual teams did not significantly change their capacity to increase or decrease their winning percentage from one year to the next. This is possibly the case because of other factors that affect whether a team improves. Some teams like the Clippers have been perennially bad due to poor ownership or lack of money, while others have remained contenders for long periods of time and have been able to recover quickly from a few bad years, such as the Lakers or the Celtics. While a new draft structure will affect the positions of these teams in the draft, it will not affect the ability of the teams to make the most of that given draft pick.

Table 3: Within Team Reg. Season Competitive Balance

VARIABLES	(6) pct	(7) pct
lag_pct	0.6566***	0.6032***
	(0.071)	(0.098)
lottery_interaction	0.0593	0.0290
	(0.095)	(0.106)
weighted_interaction	-0.0071	-0.0530
	(0.077)	(0.103)
lottery	-0.0211	-0.0054
	(0.051)	(0.057)
weighted	0.0047	0.0311
	(0.039)	(0.049)
Constant	0.1722***	0.1963***
	(0.035)	(0.046)
Observations	782	782
R-Squared	.053	.011

Clustered standard errors in parenthesis
*** p<.01, ** p<.05, *p<.1

Table 4 below displays the playoff wins and playoff round regressions. The first regression using the playoff round that each team attained in each year showed that the playoff round attained the previous season is positively and significantly correlated with the round reached this season, as reaching 1 higher round the previous, on average, increases this year's playoff round by .52 rounds. However, neither of the interaction variables for the introduction of the lottery or the change to the weighted lottery was significant, meaning that the correlation between previous year's playoff round attained and current year's playoff round did not change significant after those league changes.

The regression using playoff wins had similar results. The variable for previous year's playoff wins was positive and significant, with 1 additional playoff win the previous season increasing this year's playoff wins by .49 on average. However, the interaction variables were once again insignificant, so the changes to the draft did not affect the relationship between previous and current year's playoff wins.

Table 4: Within Team Playoff Competitive Balance

	(1)	(2)
VARIABLES	playoff_round	playoff_wins
lag_playoff_round	0.5173***	
	(0.098)	
lag_playoff_wins		0.4887***
		(0.087)
playoff_rd_lot	-0.0363	
	(0.110)	
playoff_rd_weight	-0.0765	
	(0.101)	
playoff_wins_lot		0.0313
		(0.131)
playoff_wins_weight		-0.0947
		(0.086)
lottery	0.0269	-0.0070
	(0.179)	(0.030)
weighted	-0.0077	0.0106
	(0.143)	(0.026)
Constant	0.6068***	0.0980***
	(0.136)	(0.026)
Observations	782	782
R-Squared	.318	.281

Clustered standard errors in parenthesis
*** p<.01, ** p<.05, *p<.1

Attendance Result s - Without Ticket Price and Unemployment

Table 5 shows the attendance results without ticket price and unemployment in the model. The model controls for winning percentage and league wide balance, so I am looking at the "excitement factor," or an increase in attendance due to pure excitement from being in the lottery or hype caused by the lottery. The fixed effects attendance regressions displayed a significant connection between the addition of the draft lottery and total team attendance. Lottery and non-lottery teams seem to have been affected in a significantly different way after the league instituted the lottery. The coefficient of lottery team on attendance is 34,200, which would indicate that a team participating in the lottery would have an attendance of 34,200 larger over the full season, than a team that did not participate in the lottery all else held equal. Pick differential has a coefficient of 3,407, which means that a team with a lottery pick one higher than would have been expected in a worst-to-first format would increase its attendance over an entire season by 3,407 over a team with the same selection as would have been expected. Both of these variables have a statistically significant effect on attendance. Since the lottery pick for each team is controlled for, this significance is not simply capturing the effect of having a higher draft pick on attendance.

Table 5: Attendance Models without Ticket Price and Unemployment

VARIABLES	(1) attend (fixed effects)	(2) ln_attend (fixed)	(3) ln_attend (random)	(4) ln_attend (fixed)
pct	194,328.6729**	0.3561**	0.3683***	0.2508**
	(82,984.642)	(0.139)	(0.138)	(0.092)
lag_pct	182,201.9365***	0.3592***	0.3731***	0.1569**
	(25,551.841)	(0.070)	(0.070)	(0.072)
new_arena	58,463.4686***	0.0998***	0.0979***	0.0689***
	(13,919.951)	(0.024)	(0.024)	(0.019)
nba_lockout	-260,052.6779***	-0.4782***	-0.4775***	-0.4788***
	(9,395.634)	(0.019)	(0.020)	(0.015)
nhl_lockout	2,095.6085	-0.0002	0.0038	-0.0045
	(8,093.322)	(0.014)	(0.015)	(0.012)

new_team	135,649.9591***	0.2339***	0.2169***	0.1335***
	(44,215.948)	(0.064)	(0.066)	(0.045)
relo	-8,597.4473	-0.0188	-0.0371	-0.0766
	(28,822.763)	(0.058)	(0.069)	(0.046)
all_nba	2,321.3223	0.0054	0.0076	0.0338*
	(10,032.364)	(0.016)	(0.017)	(0.019)
pdiff	90.0230	0.0002	0.0002	0.0000
	(58.638)	(0.000)	(0.000)	(0.000)
oeff	-4,113.6221	-0.0091	-0.0075	-0.0055
	(4,853.343)	(0.010)	(0.010)	(0.009)
deeff	7,356.2040	0.0146	0.0129	0.0042
	(4,496.052)	(0.009)	(0.010)	(0.010)
comp_balance	936,678.1***	1.7741***	1.8107***	0.7991
	(214,316.5)	(0.3900)	(0.3805)	(0.4964)
actual_order	486.1864*	0.0008*	0.0008**	0.0009*
	(281.323)	(0.0004)	(0.0004)	(0.0004)
wchamps	291.9636	-0.0005	0.0000	-0.0045
	(1,492.720)	(0.002)	(0.002)	(0.003)
ln_capacity	165,096.8297***	0.2331***	0.2547***	
	(55,278.321)	(0.078)	(0.073)	
ln_pop	-6,185.2546	0.0948	0.0152	0.1817**
	(49,392.853)	(0.142)	(0.026)	(0.074)
ln_income	198,521.1295***	0.3320***	0.3474***	0.1879***
	(26,149.792)	(0.055)	(0.034)	(0.051)
all_star_diff	601.5179	-0.0002	-0.0001	-0.0039
	(2,483.385)	(0.004)	(0.004)	(0.003)
lot_team	38,200.3383***	0.0896***	0.0890***	0.0466***
	(9,012.574)	(0.020)	(0.021)	(0.016)
pick_diff	3,407.7024*	0.0077**	0.0072***	0.0044
	(1,686.522)	(0.003)	(0.003)	(0.003)
pct_full				0.7622***
				(0.193)
Constant	-3.4632e+06***	5.2619***	6.0864***	7.9670***
	(744,998.573)	(1.754)	(0.742)	(1.038)
Observations	752	752	752	752
R-Squared	.6034	.5330	.6075	.5113

Clustered standard errors in parenthesis
*** p<.01, ** p<.05, *p<.1

In the initial fixed effects regression with a linear dependent variable, many variables were significant but a large portion was also insignificant. Both current and previous year's winning percentages were positive and significant at the 10% level meaning that an increase in either of those percentages will lead to an increase in attendance. The coefficient on current winning percentage was 194,329, which is fairly economically significant with an elasticity of 0.153. Previous year's winning percentage has a coefficient of 182,202, which shows an economically significant change in attendance with an elasticity of 0.143. Attendance was also significantly affected by being a new team or having a new arena, which is consistent with Schmidt and Berri (2004), who found a similar relationship. The coefficient on the new team variable was 135,650. Therefore, all else equal, a team that is in its first five years in the league will have a 135,650 greater attendance, or 3,306 more people per game. Being in the first five years in a new stadium had a coefficient of 58,463, so teams in recently built arenas will have 58,463 more people, or 1,426 per game. These findings are similar to those of Leadley and Zygmont (2005), who found that the "honeymoon effect" of moving into a new stadium is real and significantly increases attendance. Relocating, on the other hand, was not found to be statistically significant.

Changes that the lottery may have had on competitive balance were controlled for in two ways. The competitive balance variable is included in the model to control for league-wide balance within a season, and balance across seasons and within individual teams is controlled for by including the lagged winning percentage. The variable for league-wide competitive balance during the season was significant and positive, indicating that a higher degree of parity within the league leads to greater attendance, all else equal. This is consistent with the findings of most competitive balance research, including Schmidt and Berri (2001). The dummy variable for the NBA lockout is significantly negative, as fewer games that season led to smaller total attendance figures. The NBA lockout season had a coefficient of -260,052, so the season during which the lockout took place saw teams have decrease in attendance of 260,052. This makes sense, as the lockout led to fourteen home games being missed per team, and 260,052 equates to 18,575 attendees per game missed, which is a typical attendance figure for a team during a game. The NHL lockout was not found to be significant. The season during the NHL lockout had similar attendance to all other seasons despite the lessened competition. This is possibly because NBA and NHL fans are generally different fans, so one sport being missing does not largely affect the other. Further, if NBA teams in cities with NHL teams were already selling out or close to selling out, the lack of a hockey season could not possibly drive attendance up. Stadium capacity was also strongly significant. A one percentage point change in capacity leads to a change in attendance of 165,097 across the entire season, all else equal.

Demographic level variables had mixed results. Metro-area population was shown to have an insignificant affect on team attendance, but the natural log of per capita income was significant with a coefficient of 198,521. This means that a one percentage point change in per capita income in the city of a team leads to an increase in attendance of 198,521 for that team.

Team efficiency variables were found to be insignificant. Point differential, offensive efficiency, and defensive efficiency were all shown to have little effect on attendance. Weighted championships were also insignificant, meaning a team with more championships, weighted to value recent championships greater, showed little affect on attendance. This could be because teams that have won recent championships are likely still good, and that effect is captured in the current and lagged winning percentages. This result differs from Schmidt and Berri (2004), though they use a different set of years in their study. Additionally, they use ticket price and unemployment in their model, and in the models below with ticket price and unemployment, weighted championships become significant.

Results were very similar in the log-linear model. The lottery variable and pick differential variable both remain significant, with a lottery team having a .09 percentage point greater attendance than a non-lottery team and a team with a pick one higher than it would have with the lottery having a .008 percentage point greater attendance, *ceteris paribus*.

The dummy for the NBA lockout is still significant, and the dummy for the NHL lockout remains insignificant. Also similarly to the previous model, the coefficients on the dummy for a new team and a new arena are positive and significant, signifying that a team in its first five years has 23% greater attendance and a team in a new stadium has 10% greater attendance, all else equal. The variable for stadium capacity also remains significant and positive, showing that a one percentage point increase in capacity leads to a .23 percentage point increase in attendance. Per capita income is significant, too, with a one percentage point increase in income resulting in a .33 percentage point greater attendance. No other variables in this model are significant at the 10% level.

In the models above, the coefficient on stadium capacity is very high, accounting for a large portion of the change in attendance from year to year. To attempt to control for this, I tried a final model in Table 5 which includes a variable for the percent of the arena that is full but does not include the stadium capacity variable. In this model, many variables show different levels of significance than in the other models. The lottery team variable is significant and increases attendance by five percentage points, but the pick differential variable is not significant.

The percent of the stadium that is full has a positive and significant effect on attendance, similar to the effect that capacity had in previous models. Winning percentage and lagged winning percentage continue to be positively correlated with attendance. Many other variables maintain a similar sign and significance as in the capacity models, but a few are also more significant. The number of all-NBA players on a team became significant at the 10% level in this model. This shows that an increase of one all-NBA player leads to an increase in attendance of 3 percentage points.

Additionally, while income remains a significant variable in the model, population is also significant which was not the case in the previous models. A one percentage point increase in population leads to an 18 percentage point increase in attendance, while a one percentage point increase in income leads to a 19 percentage point increase in attendance. Population could be more significant in this model because capacity could take into account population, as areas with greater populations may build larger arenas to fit the larger number of people.

Being that the NBA sells out such a large portion of its games, determining which factors affect attendance and to what extent can be difficult. Selling out also leads to similar attendance numbers each year for many teams; if a team is limited in ticket sales by its stadium capacity each year, then its attendance numbers will be similar every year, as they will be very close to the capacity each game. In addition, under a few circumstances only average attendance data over a span of few years was available. While these cases were infrequent, the few times that yearly attendance data were not available limit the ability of the model since the exact change in attendance from one year to the next is not known.

Attendance Results - With Ticket Price and Unemployment

In a model that includes unemployment but no ticket price variable, being a lottery team still has a positive and significant effect on attendance, but the difference between the actual pick and the worst-to-first pick was not significant. The attendance results, as can be seen in Table 6 below, are different in the models that include both ticket price and unemployment. Measuring the effect of the lottery is more difficult with these data because observations from the 1980s before the lottery was introduced were not available, and therefore are not included[2].

In the model with both ticket price and unemployment, neither being in the lottery nor the pick differential between where a team would have picked without a lottery and where they actually picked were significant, though this could be caused by the lack of pre-lottery data.

Both winning percentage and the previous year's winning percentage are positive and significant in these models, once again indicating that a higher winning percentage leads to greater attendance. Additionally, a new arena and a new team both lead to greater attendance, as was seen in the previous models. Capacity is once again significant, as a 1% increase in capacity increases attendance by 359,086 across the entire season. The NBA lockout season significantly decreased attendance as was the case in the models without unemployment and ticket price, but the models in Table 6 also show the NHL lockout season to have significantly increased attendance, which was not the case in the previous models. The NHL lockout season had an increase in attendance of 16,381, or 2.7 percentage points in the model with the natural log of attendance. Weighted championships were also significant in all models in Table 6, meaning that teams with more championships weighted towards more recent years had an increase in attendance, *ceteris paribus*. All other variables were insignificant in those models, including

[2] To test for whether ticket price and unemployment being excluded from the model significantly affected the results or whether the change in results is attributable to the smaller sample size without pre-lottery data, I ran a regression excluding those two variables from the model, but only using the 522 observations that include both unemployment and ticket price data. The results to the regression without ticket price and unemployment using only the 522 observations where those variables were available (in Table 6) show very similar results to the results to the regressions with ticket price and unemployment included using those 522 observations. The exact same variables were significant in each of the models in Table 6 with the exception of income, which was only significant in those models without ticket price and unemployment. In general, the models using 522 observations that did not include those variables were much closer to the models that did include those variables than those models which excluded them but utilized the full 819 variables. This indicates that the lack of significant results for the lottery and draft pick change is caused by the small sample and lack of observations before the institution of the lottery and weighted lottery. The lack of significant results on competitive balance in the models with only 522 variables further show that these results do not have enough observations to be reliable. While the models in Table 5 all showed that an increase in competitive balance increases league attendance, which is consistent with most literature on competitive balance, the models in Table 6 show no significance.

competitive balance which had been significant in all of the models that excluded ticket price and unemployment.

The last model which included the percentage of the stadium that is full instead of the stadium's capacity produced mostly similar results. The variable for percent of the stadium that is full was positive and significant, meaning a higher percent of the stadium that is full increases attendance as would be expected. The NBA lockout remains negative and significant, but the NHL lockout is now also significant, causing a three percentage point increase in attendance. The variable for a new arena is also significant at 10%; it has a coefficient of .037, so attendance increases by almost four percentage points for teams with a new arena, all else equal.

Table 6: Attendance Models with 522 Observations

VARIABLES	(1) attend (fixed effects)	(2) ln_attend (fixed)	(3) attend (fixed)	(4) ln_attend (fixed)
pct	165,161.4**	0.2944**	170,450.5**	0.3025**
	(78,107.98)	(0.119)	(81,380.61)	(0.1225)
lag_pct	91,240.19***	0.1431***	101,322.8***	0.1582***
	(32,885.23)	(0.0485)	(33,844.38)	(0.0500)
new_arena	21,227.78**	0.0340**	25,744.23**	0.0406**
	(9,203.085)	(0.0152)	(9,658.315)	(0.0165)
nba_lockout	-269,632.9***	-0.5033***	-266,708***	-0.4992***
	(9,478.09)	(0.0173)	(9,686.729)	(0.0181)
nhl_lockout	16,381.05**	0.0267**	16,104.71**	0.0264**
	(6,955.32)	(0.0101)	(6,923.907)	(0.0100)
new_team	111,818.6***	0.1643***	110,424.7***	0.1624***
	(34,943.75)	(0.0516)	(35,305.6)	(0.0516)
relo	805.8806	0.0206	6,343.132	0.0290
	(24,728.48)	(0.0346)	(25,902.75)	(0.0368)
all_nba	-10,538.95	-0.0195	-9,051.13	-0.0173
	(8,330.009)	(0.0128)	(8,535.621)	(0.0132)
pdiff	53.5866	-0.0000	58.7514	-0.0000
	(38.79426)	(0.0001)	(40.5254)	(0.0001)
oeff	-492.6892	0.0056	-1,334.13	0.0044
	(3,537.519)	(0.0062)	(3,874.986)	(0.0066)
deeff	5,199.462	0.0004	5,517.287	0.0009
	(4,071.049)	(0.0065)	(4,356.716)	(0.0068)
comp_balance	-68,210.68	-0.1765	-64,191.04	-0.1713
	(203,222.7)	(0.3344)	(202,542.8)	(0.3306)

actual_order	86.0996	0.0002	92.0006	0.0002
	(253.721)	(0.0004)	(251.045)	(0.0004)
wchamps	2,427.869***	0.0031**	2,638.356***	0.0034**
	(835.2231)	(0.0013)	(851.8874)	(0.0014)
ln_capacity	359,086.4***	0.5092***	371,009.9***	0.5266***
	(91,803.63)	(0.1405)	(96,009.73)	(0.1461)
ln_ticketprice	37,347.52	0.0558		
	(26,373.9)	(0.0397)		
ln_pop	-71,118.98	-0.0941	-66,832.03	-0.0873
	(59,844.1)	(0.1016)	(59,398.6)	(0.1022)
ln_income	40,799.65	0.0709	75,293.83**	0.1214**
	(33,484.68)	(0.0466)	(30,285.57)	(0.0469)
ln_unemployment	-1,044.402	-0.0006		
	(14,945.9)	(0.0214)		
all_star_diff	2,313.563	0.0030	2,613.345	0.0035
	(2,679.045)	(0.0041)	(2,670.305)	(0.0041)
lot_team	4,871.767	0.0078	4,170.39	0.0070
	(9,381.191)	(0.1458)	(9,348.684)	(0.0145)
pick_diff	231.9082	0.0006	5.0052	0.0003
	(2,173.848)	(0.0030)	(2,098.455)	(0.0030)
Constant	-2,962,814***	8.0403***	-3,323,438***	7.5005***
	(1,004,199)	(1.5955)	(1,018,106)	(1.6098)
Observations	522	522	522	522
R-Squared	.4987	.5706	.4955	.5662

Clustered standard errors in parenthesis
*** p<.01, ** p<.05, *p<.1

VII. Conclusion

This paper includes analysis that addresses two questions: whether the introduction of the NBA draft lottery and the change to a weighted lottery had an impact on the competitive balance within the league and whether teams that participate in the draft lottery receive an increase in attendance the next season caused specifically by their participation in the draft lottery. The results on both accounts were mixed when running different regressions. The first competitive balance regressions using the standard deviation of wins within the league showed that changing the lottery to a weighted format decreased league-wide parity, but showed no significance to the original introduction of the lottery. Meanwhile, using the competitive balance ratio which incorporates both team and league-wide balance, both the introduction of the lottery and the change to a weighted lottery proved to decrease balance. Finally, using both playoff measures and regular season record measures, neither change in the lottery format showed an effect on team-level balance.

As for attendance, results differed when a variable for ticket price was included, likely because ticket price data were not available for the years before the lottery. Without that ticket price variable, lottery teams had greater attendance than non-lottery teams, and attendance also increased as a team received a higher pick than its regular season standings would indicate in a worst-to-first format. However, when including ticket price, both of these variables became insignificant.

While the results of both sections are mixed, they still have implications for the NBA and other professional sports leagues. Though the lottery decreased balance and greater competitive balance is generally associated with higher attendance, attendance still increased for teams in the lottery strictly as a function of being in the lottery. Sports leagues should be aware that, as Williamson (2010) displayed and these results supported, if their intention is to prevent tanking, a lottery will not succeed. However, the publicity that the lottery brings for teams with a draft pick outdoes the lesser league balance and generates greater attendance. So for a league trying to increase profits, a draft lottery can be useful to increase the attendance of those teams that are least likely to have great ticket sales; namely, those that do not make the playoffs. The NHL has already moved to a draft lottery format, and it could be a trend for other leagues in the future.

From here, the study could be furthered by looking into whether the introduction of the draft lottery has a similar effect in the National Hockey League (NHL). If similar results are found in the NHL, it could provide further evidence in support of other leagues moving to a draft lottery if they want to improve attendance numbers for teams that do not make the playoffs. It also may be worth exploring the impact of different selection numbers on team attendance. For example, how much more does attendance increase, if at all, from having the first draft pick as opposed to the second pick, or the second pick as opposed to the third. This would give an indication of not only the significance of moving up one pick, but the significance of moving up a pick at each spot in the lottery.

Table – Changes in Attendance

	Lottery Team	Increased Pick	New Arena	New Team
Overall Change in Attendance	38,200	3,408	58,463	135,650
Change in Per Game Attendance	932	83	1,426	3,309
Percentage Point Change	0.090	0.008	0.1	0.234

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