

The Winner's Curse in the Market for Free-Agent NBA Players

In a common value auction with imperfect information bidders offer their bids, individually and secretly, for goods or services estimated from their expected return. The winner offers the highest money and is also the most optimistic bidder in the auction war. Logically, the true value of the product should be closer to the mean value of offers. Since the winning bid is usually greater than the mean bid, winners have a greater tendency to pay more than the true value. In other words, the winners have greater chance to overvalue the product. This phenomenon is called a "winner's curse."

The winner's curse theory originates in natural resource economics, under the study of bidding war for oil fields (Capen, Clapp, & Campbell, 1971). It has also been applied to a number of studies in sport economics literature, many of which focus on the biddings for hosting mega sport events such as the Olympics, the FIFA World Cup, and the Super Bowl (Baade & Matheson, 2002, 2004, 2006; Mules & Faulkner, 1996; Ritchie, 1984; Ritchie & Aitken, 1984; Ritchie & Smith, 1991). The results almost always point into the same direction. Hosting countries (or cities) overspend on the events and make a lower than expected, or even negative return. This implies that there is a winner's curse in mega sport event auctions.

In another respect, major league teams almost always participate in bidding wars for players due to a limited number of talented players. Salaries of major league players are some of the highest paid occupations in the United States. There are two possible causes for such high wages: monopoly power of players from super star power and/or the player union, or bidding wars among teams.

Rosen (1981) is the first to present a theoretical framework on the Economics of Superstars. In this pioneer work the author shows that superstars enjoy premiums of their superior talent. This reward is not linearly but multiplicatively related to talent. Audience's have higher demand for talents, so players with more ability have a larger market to capitalize on their strengths. The bigger the market size the more income the players get, because the teams that acquire such talents gain higher returns. Furthermore, as demand expands, the concentration of income tends to be larger for star athletes if the demand is elastic to talent.

There are various studies that explore the winner's curse in the player market. Blecherman and Camerer (1996), Burger and Walters (2008), and Cassing and Douglas (1980) use data from the Major League Baseball (MLB) from different time spans and different techniques; every study discovers the winner's curse in the teams' bidding for player process. Massey and Thaler (2013) study the same issue in the National Football League (NFL) drafting behavior of teams and discover supportive evidence.

The National Basketball Association (NBA) is one of the most famous sport industries in the United States. Star players' salaries are tremendously high. Almost every team has at least one star player. In 2015, the average NBA player's salary was \$5.15 million. By far the NBA players earn more than any other professional sport players. Eschker, Perez, and Siegler (2004) explore the winner's curse problem in the NBA, focusing on international players and revealing that international players were overpaid by teams. There existed the winner's curse in the NBA during the 1996-97 and 1997-98 seasons, at the beginning of the influx of international players. The curse, however, disappeared afterward. Groothuis, Hill, and Perri (2009) find that there is a great

uncertainty and false positives in players' performance from a drafting system where teams overestimate the performance of players. They conclude that this might not be a result of the winner's curse, rather it is because that there are very few talented players. If the teams want a chance to win over these players, they have to invest in them just like buying a lotto where they rely on the accuracy of talent evaluation; but the chance is of winning the prize is as uncertain as the uncertainty of performance.

The aim of this study is to evaluate whether NBA teams can accurately predict the true value of their players or are falling into the trap of the winner's curse. The finding from this study should provide some insightful information to teams' managers about their bid strategies. If such a curse persists, the managers should learn how to avoid the curse by discounting all bids accordingly. Also, it should help shed some light on the theory of winner's curse under the real world circumstance. The structure of this paper is as follows. The following section presents theoretical background of the winner's curse. Section 3 presents data sources and methodology implemented in this study. Fourth section provides empirical results. The conclusion and recommendation are in the last section.

Theoretical Background

Capen et al. (1971) brought the processes of closed-envelop competitive bidding to light, using an example of competitive bidding for a petroleum field in the Gulf of Mexico. The authors present that the return on investment often does not meet the expectation of firms. The return was either lower than expected or even became negative, which made average return on investment become negative. Each bidder has different information that leads to different expected return on investment. Even if the information is exactly the same, expectations are different among bidders due to different perceptions. This leads to

varying expected return, which can be too high or low and almost no chance of being exactly the true value of the object in auction. The winning firm of the competitive bid is that which has the highest expected return or overestimates the true value. The firm is less likely to win a bid if it was to undervalue the object. This is the so-called the “winner’s curse.” From the simulation method of an expected winning bid probabilistic model presented in Capen et al. (1971), it seems that the expected winning bids tend to be higher when there is more information, when there is more uncertainty about true value and when there are more bidders. The author suggests that once bidders realized the existence of the winner’s curse, they should lower their bids accordingly.

Thaler (1988) defines the winner’s curse into two versions: the winner receives negative return on investment and the winner receives less than expected return on investment. Both versions of the curse leave the winner disappointed. Thaler further explains that economic theories normally assume rationality, while it is difficult in such a competitive bidding setup because the expected value of an investment is indeed conditioned on winning the auction. Firms tend to bid more aggressively as the number of bidders increases. Meanwhile, winning an auction war against more bidders increases the chance of the firm overestimating the true value.

The early experiment on the winner’s curse was conducted by Bazerman and Samuelson (1983). A coin-filled jar worth \$8 was the auction object while subjects, 419 MBA students in 12 microeconomics class at Boston University, did not know the true value of the object. The study discovered that in the closed-envelop auction environment, the mean estimated value of the object was approximately \$3 below the true value.

Nevertheless, the mean winning bid was \$2 above the true value of the object. This serves as evidence of the winner's curse.

Several experimental studies followed such as those of Kagel, Harstad, and Levin (1987), Kagel and Levin (1986), and Samuelson and Bazerman (1985). The results point in the same direction that there exists winner's curse. Although the curse is realized and can be eliminated as bidders gain more experience and knowledge, it is difficult to avoid such a curse due to complexity of valuation of the product's true value and bidding competition. However, laboratory studies usually face criticisms about the realism. Therefore, various field experiments were conducted; most encounter evidence of the winner's curse (Hendricks & Porter, 1988; Roll, 1986; Varaiya, 1988; Varaiya & Ferris, 1987).

Cassing and Douglas (1980) study the winner's curse theoretically and explore real world phenomena using the Major League Baseball (MLB) data. The authors develop a theoretical study based on a noncompetitive environment where teams bid for talent from a player who is the monopoly of his own talent which has the marginal revenue product (MRP) equal to $B/2$. The teams' expected value of the MRP is assumed to have a uniform distribution with the range between 0 and B. In other words, sometimes the MRP will be underestimated and sometimes be overestimated. If there is only one team that bids for players several times, on average, the bidding offers will be equal to the players' MRP. In competitive environments with more than one team involved in the bidding war, on the other hand, teams that correctly estimated the true value are usually not the winner. The winners are usually the teams that overestimate the MRP. Although teams have identical information about players, they can still offer different bids due to some human element in digesting information.

Assume that there are n bidding teams where every team has an identical uniform distribution for MRP on the interval $[0, B]$ with mean $B/2$ and in order to win the bid, the winner must offer $\$x$ to player. This means that there will be $n - 1$ teams that lose the bidding war. Hence, the probability that all but one team bids less than x is $(x/B)^{n-1}$. Given K is a constant necessary to make $h(x)$, the p.d.f. of the winning bid, integrate to 1, $h(x) = K(x/B)^{n-1} (x/B)$. In the case where $K = n$, we can write an equation of the expected winning bid (EWB) as

$$EWB = \int_0^B xh(x)dx = \int_0^B n(x/B)^n dx = [n/(n + 1)]B$$

It can be seen that EWB will equal to MRP ($B/2$) only when there is one team in the bid and exceeds MRP when $N \geq 2$. The size of EWB increases and approaches B as n increases. In conclusion, free-agent players tend to be paid more than their true value under competitive bidding environment and the size of extra pays tend to be bigger as the number of bidding teams increases.

Cassing and Douglas find that teams overpay players. However, the authors conclude that selection bias of samples could result in such finding. Only better players tend to switch teams, and vice versa. As a result, players with uncertain performance, who are not represented in the samples, tend to stay with their former team; the good ones are the ones that move and create higher value for their new teams. Burger and Walters (2008) use a newer data set and a more sophisticated technique to measure performance and discover the same issue. The authors conclude that, with available information on players, especially about risk, teams still fail to avoid the winner's curse when they are faced with complex valuation problems such as talent; teams continued to overvalue players. Massey

and Thaler (2013) similarly study the same problem in the National Football League (NFL) teams' drafting behavior. The finding follows those of the MLB studies that performance is also overvalued in the NFL.

Pepall and Richards (2001) use a game theoretical framework to explain such phenomena under a Bertrand duopolistic setup where two teams, i and j , are competing downstream in a price competition of output that involves the usage of a superstar and upstream where the two teams compete in a bidding war for a superstar. At equilibrium, if the ticket price of one team is positively correlated with the presence of a star in another team, a price war begins and both teams are worse off. If the ticket price is negatively affected by the presence of a star in another team, star player softens competition and both teams benefit, except that the team which hires the star receives less profit. In other words, there is a tendency for the winner's curse to occur in the market where price of end product negatively corresponds to the present of stars.

Data and Methodology

Winner's curse in the player market occurs if the winner of the bid has an expected value of a player that is greater than his real value. The expected value of a player is the return the team estimated that they will get from hiring that particular player. For any rational team the pay will not exceed the player's expected generated income. In mathematical expression:

$$w_i(MPL_i) \leq MRP_i$$

where $w_i(MPL_i)$ is the offered player's salary based on his expected marginal product of labor (MPL) which, in sports, is the marginal win produced by player, and MRP_i is player's marginal revenue product or his contribution to team income in dollar term.

However, there is an uncertainty about the true value of the player's production that makes some teams, although rational, more likely to overvalue the player and offer a wage that is above his MRP. A team falls a victim of the winner's curse if they win the bid while their expected value ($E(MRP)$) of the player more than the true (average) value (MRP).

In bidding process with almost identical information, the expected value of a player should be similar between teams. Hence the distribution of expected value is known to the bidders. The bid distribution does not reveal the underlying true distribution of MRP. To guarantee that they will be able to sign a player, with no information about other teams' offers, teams have to offer their best possible contract they can under the profit-maximizing condition. The offered salary needs not to be equal to the player's expected value, but it needs to be above other teams' offers in order to win. Some teams might offer bids that are lower than the true value, and vice versa, but on average, the bids should be close to the true value. In other words, the part of player's salary that is determined by expected marginal product ($E(MP)$), must be equal to player's expected value ($E(MRP)$) perceived by the competitive auction bidders. The winners' $E(MRP)$ s, as a result, are usually higher. It is important to stress that the wage mentioning here is only a partial wage that is determined by player's expected production and not the actual wage that may include other aspects of the player such as age, experience, charisma, union power, team power, hedging against the winner's curse, and so forth.

$$w_i/E(MPL_i) \leq E(MRP_i)$$

From labor economic theories, $w = MC \times MPL$ for profit maximizing business in competitive market. Since $MRP = MR \times MPL$, one can rewrite the previous equation as

$$MC \times E(MPL) \leq MR \times E(MPL)$$

Divide both sides of by $E(MPL)$:

$$MC \leq MR$$

The salary is less than or equal to expected marginal revenue product, hence, marginal cost is less than or equal to marginal revenue. This is true either under the perfect competitive environment or the noncompetitive environment where the bargaining power of the players and the teams are equal and cancel out each other. The true value of a player cannot be directly observed because it involves many perspectives; some of which cannot be measured. Good examples include leadership, personality, and similar characteristics. Although the the estimated marginal revenue product (MRP) can be predicted if MR and MP are known. As a result, this study assumes that teams have information about players' the mean marginal product and its distribution. However, teams still face uncertainty of performance due to the variance in performance, which is different from player to player. Also, teams already have a plan on how to use the players in their games. For example, they have expectations about how much time the players will be put on the court throughout the contract period.

Previous studies of the winner's curse in bidding for players almost always compare singular wages with MRP of players to justify whether there exists the winner's curse or not. As mentioned earlier, considering that there are many factors determining wage and the conclusion about winner's curse drawn from the fact that wage is greater than MRP might not be realistic. As a result, this study focuses on the evaluation of MC and MR of wins that are contributed by players to reach the conclusion about the winner's

course. There are three main steps of the estimation. The data used in all the steps must be chosen carefully to best fit the methodology. The data can be separated into team level and individual player level data. The descriptive statistics of the data used in this study is in Table 1.

Evaluation of Players' Contribution to Wins

The first step of the analysis is the calculation of players' contribution to teams' wins. The win score (WS) method introduced by Berri (2008) is implemented in this study. The main advantage of WS is that it measures players' production in term of numbers of wins generated to a team which makes it possible to summarize players' performance into one unit of tangible measurement, wins. The method involves two main steps: the calculation of players' action on court and the actual win contribution of each player to his team in each season. It shall be noted that win score is selected in this study not because it best predicts player performance nor does it highly related to wages; it is chosen mainly because it directly illustrates players' contribution as number of wins produced which is more suitable for the study of MRP. The individual performance statistics are required for the following steps.

Both team-level and individual-level performance data for the NBA 2004/2005 season through the 2014/2015 season are obtained from www.basketball-reference.com. It should be noted that players who appeared less than 20 games per season or spent time on court less than 12 min per game were excluded due to their minimal impact on the games. A total of 1,410 qualified players, free agents, and nonfree agents, are included in the first step of WS evaluation. This is to get the most accurate values of players' actions, since every player shares some part of contribution in games. Every analysis after the evaluation

of WS only uses 691 free-agent players with multiyear contracts because they can better represent the competitive market. This is the main focus of this study. As for team-level data, since there are 30 teams across 11 seasons, the total of 330 observations are used.

It is important to understand that in the Berri (2008)'s version of WS, players' contributions are evaluated only for each particular season. Despite being a useful tool to evaluate player's production, the season-specific nature of the variable is a drawback for cross-season studies. In this study WS need to be compared across season. As a result, some adjustments are necessary.

In the final step of the calculation for WS, Berri divides player's Wins Produced per 48 min played (WP48), which is calculated from performance statistics, by 48 and multiplies by the actual minutes played (MP) to get the win score, WS. For the analysis of this study, WP48 for every player for each season are estimated and averaged across the years of contract, player-by-player. So the WP48 used in this study is the contract-length average WP48 of each player. The variance of WS is calculated per player from the contract-length average WS. There are 804 free-agent players whose names appeared in the roster for the 2004/2005 to 2014/2015 season that are qualified from the selection criteria. However, in order to calculate the variance of performance, which is crucial to this study, only players who signed multiple-year contracts are included and the sample size reduces to 691.

In this study, it is assumed that teams know the contract length-average WP48 and variance of WP48 of each player as they can observe performance of every player across several seasons, and that they also know how much time each player will be placed on court. After dividing the contract-length average WP48 by 48 and multiplying by contract-

length average minutes played of that player, the expected WS of each player is obtained and assumed to be known by team prior to bidding process.

To ensure that the use of expected WS in this study will be consistent with the actual WS (denote as AWS) calculated for each player for each season from the Berri (2008) method, the correlation between WS and AWS for 691 free agents is calculated. It appears that there is a 90.28% significant relationship between the two variables. As a result, the implementation of expected WS in this study should not significantly impact the results.

Figure 1 is the histogram of expected win score of free-agent players. The distribution is right-skewed. The shorter left tail implies that there are not many “bad” players among the free-agent NBA players. The longer right tail indicates that superstars are hard to find. However, it should be noted that the greater wins contributed to team does not come solely from the superior performance as measured by WP48, but also from the longer minutes played.

Figure 2 shows that the variance of WS is very rightly skewed. This implies that there are only a small amount of players with inconsistent WS. This is in line with the 70% correlation of players’ WS from one season to another season, which implies the consistency of players’ performance across the seasons.

Evaluation of Marginal Cost of Win

The marginal product of each free-agent player, namely expected win score (WS), from the previous steps are used for the calculations of marginal cost (MC) and marginal revenue (MR) of win. The MC of wins is defined as the amount of money teams spent in order to win one extra game. Since teams use players to produce victories, salaries of a

player determine the MC. As teams only have limited spots in the roster, in order to win more games, rather than a higher quantity, quality of player is required. Better players cost more to the team. This study assumes that MC of WS is constant. The salary data came from www.basketball-reference.com. Since many players sign multiyear contracts, the contract-length average salary is used in the analysis for simplicity. Other costs associated with wins are neglected as we only consider the cost of wins the teams spent on players.

As expected WS presents the expected production of wins each player produced, it is the expected marginal product (E(MPL)) of that player. Once the MP is calculated, the “MRP realized wage,” the base salary that is determined by player’s MRP or $w|E(MPL)$ can be determined. The use of WS especially the assumption that the realized MP is known prior to the contracts were signed might not be realistic. However, as stated in Capen et al. (1971) that a better technology used for estimating the true value of product, in this case WS, might narrow the uncertainty but it does not necessarily change the expected value.

To control for other characteristics of players that might affect the salary negotiations, a regression of salary as a function of player’s MP, controlling for other player’s characteristics, can be performed using the following equation.

$$w_k = \alpha_0 + \alpha_{WS} WS_k + \alpha_{VarWS} VarWS_k + \sum_{m=3}^n Z_{jk} \alpha_m$$

Where w_k is player’s salary; WS_k is player’s expected win score, $VarWS_k$ is variance of player’s win score that captured uncertainty in the marginal product of player, Z_k is other characteristics of player’s: age, age-squared, experience, height, weight, position played, and superstar status (measure by all-star game appearance). The estimated coefficient α_1 is

the MC of wins. While WS and VarWS comes from the previous step, the rest of the information is from www.basketball-reference.com.

Consider the histogram of free-agent salary in Figure 3, one can observe a right-skewed distribution. This indicates that only a small portion of players receive higher pay. There is 39.56% significant correlation between salary and expected performance of free-agent NBA players. This indicates that teams do realize players' contributions and reward them accordingly.

Evaluation of Marginal Revenue of Win

The next step of this study is to evaluate the value of player as the contribution that each player makes to the teams' revenue. The pioneer work on monetary valuation of wins is a study of Scully (1974). The calculation involves the estimation of marginal revenue (MR), or in the specific term for sport teams, marginal wins value (MWV) for each team. The MWV is the revenue the team expected to gain from winning one extra game. Rascher and Rascher (2004) indicate that team's revenue is a function of market characteristics and team characteristics. Overall, one can say that there are various factors determining revenue of a team.

To study this topic, we need team-level data. There are many factors contributing to revenue. The most important factors are winning percentage of current and previous seasons. Other determining factors include extra game played after the regular season (measured by playoff appearance), market size (measured by population in the metropolitan area where the franchise located), stadium capacity and year-specific dummies to account for economic impact such as inflation and industry growth. The winning percentage data are gathered from the NBA official website (www.nba.com).

The population data are collected from www.census.gov and www.statcan.gc.ca. The stadium capacity data are published at [https://en.wikipedia.org/wiki/List of National Basketball Association arenas](https://en.wikipedia.org/wiki/List_of_National_Basketball_Association_arenas). The revenue data are collected from the 2004/2005 to 2014/2015 seasons, which are available at www.forbes.com/teams.

With our main focus on winning, we can regress a total revenue function from the following model.

$$TR_i = \beta_0 + \beta_{Win82} Win82_i + \sum_{j=2}^n X_{ij} \beta_j$$

where TR_i is team's total revenue, $Win82_i$ is number of games won per 82 games played (due to disagreements between players and teams, the 2011/12 regular NBA season was shorter than the usual 82 games) calculated by multiplying team's winning percentage by 82. To make the analysis of marginal revenue consistent, winning percentages are converted to Win82. It is defined as numbers of games won out of 82 games played., X_i is a vector of external factor affecting team's total revenue, and β_i is the MWV or the MR.

Another measure of win is team win score (team WS), which is simply the summation expected WS of every player in the particular season's roster. The team that has highest WS in the sample is the Golden State Warriors in the 2014/15 season, who won the NBA championship in that season. A 90.18% significant correlation between the team WS and Win82 indicates that the expected performance is highly correlated with the actual performance.

A 25.39% correlation between team revenue and Win82 is observed. This indicates that teams with higher revenue usually win more often. On the other hand, 21.56% correlation is predicted for team's total revenue and Team WS. This implies that there is a

slight positive relationship between teams' revenue and the cumulative expected performance of players in the rosters. The weak correlation may be a result of outliers in the sample where teams that, despite having high revenue, suffer from poor performance. There are two possible reasons: fan royalty keeps the team revenue high even the teams do not perform well; or these teams have poor resource allocation and spend too much money on bad players.

The winner's curse appears if MC is greater than MR. In other words, if α_{WS} from the estimation in salary equation is greater than β_{Win82} in the revenue equation then there is an evidence of the winner's curse.

Results

Marginal Cost of Win

This study applies win score (WS) of Berri (2008) as the performance measurement of players. The main reason is because it is directly measuring the contribution to wins of each player that can be directly interpreted as player's marginal product. In the process of calculation for WS, WP48 is estimated. WP48 is defined as wins produce per 48 min. It is evaluated from various performance statistics. A player's WS is the actual wins produced by that player in that season which is WP48 divided by 48 and multiplied by the actual minutes played.

The players' performance of current season and the season before are significantly correlated with each other (70% for WS and 72% for WP48). In this study, the contact-length average WP48 is used for calculation of expected WS and is assumed to be common knowledge among teams. Teams are also assumed to have already planned ahead of the season how much time each player will be playing. As a result, WS is known to teams. The

variance of performance is assumed to be common knowledge, but the uncertainty in actual performance remains.

The offered wage is a function of performance, variance of performance and other players' characteristics.

$$\begin{aligned}
 Salary_i = & \beta_0 + \beta_1 WS_i + \beta_2 VarWS_i + \beta_3 (WS_i \times Star_i) + \beta_4 Age_i + \beta_5 Age_i^2 + \beta_6 Exp_i \\
 & + \beta_7 Ht_i + \beta_8 Wt_i + \delta_0 Star_i + \sum_{j=1}^4 \delta_j Pos_{ij} + \sum_{k=1}^{10} \delta_k Year_{ik} \\
 & + \sum_{m=1}^{29} \delta_m Team_{im}
 \end{aligned}$$

where *Salary* is player's salary, *WS* is expected win score calculated from average WP48, *VarWS* is variance of win score, *Age* is player's age at the beginning of the season when the contract was signed, *Exp* is experience in the major league at the beginning of the season when the contract was signed, *Ht* is player's height in inches, *Wt* is player's weight in pounds, *Star* is the dummy variable for star player (= 1 if player appeared in the roster of the all-star game during the contract at least once), *Pos* is dummies for positions (where power guard is the base group in this study), *Year* is the year at which the contract was signed, and *Team* is the team-specific dummy. The heteroskedasticity is observed, so the robust standard errors are used. The result of the regression is presented in Table 2. The estimated coefficient of Year and Team are not presented in the table to conserve space.

The model can explain approximately 45.35% of the the variation in salary. This indicates that there is ample room for other factors considered by team when determining players' wage. The use of salary to compare with the marginal revenue product of players in earlier studies of the winner's curse, therefore might not be appropriate.

From the regression, Age, Weight, and Position dummies except for center are not statistically significant. On average, as nonstar player's win score increases by one game, all else being equal, his salary is expected to increase by \$236,315. To explicitly focus on the "super star," the players who received sizable contracts, the Star dummy is included into the model along with the WS-Star interaction term. The estimated coefficient of both terms are statistically significant. Star players receive a premium of \$9,693,614, on average. However, they are exploited on their superior performance as the WS-Star interaction term shows a significant negative sign. Average star players' WS is 8.67 and so they produce 5.41 more wins than average nonstar players who average WS is 3.26. One can calculate that an average star player receives a total of \$7,510,094 as a premium after discounting for their superior performance.

The variance variable is statistically significant and has a positive value. This follows the winner's curse theory that a greater uncertainty in the expected value of the product leads to a higher bid. The correlation of WS and VarWS is positive significant at 53.90% indicating that better players seem to be more inconsistent. In other words, there is a performance streak for better players.

Age is statistically insignificant but Age^2 is significant and negatively affect salary; this indicates that older players receive lower pay which should be a result of lower expected performance. The correlation of age and performance is -14.96% for the regular players (but not significant for star players). Experience is positively significant. Height also have a positive significant effect on wage.

Marginal Revenue of Win

One game produced by an average player is equal to a game produced by a star player. As a result, the returns on wins for a team should be the same no matter who generates wins. Hence, team-level data are used for the calculation of marginal wins value (MWV), in contrast to the individual player data used in the calculation of the marginal cost. Heteroskedasticity was encountered but was corrected after using robust standard errors. The model for estimation is

$$TR_{it} = \alpha_0 + \alpha_1 Win82_{it} + \alpha_2 Win82_{it-1} + \alpha_3 Pop_{it} + \alpha_4 Cap_{it} + \gamma_0 Playoff_{it} + \gamma_1 Champion_{it} + \sum_{j=1}^{10} \gamma_j Year_i$$

where TR_{it} is team total revenue, $Win82_{it}$ is number of wins per 82 games, $Win82_{it-1}$ is the number of wins per 82 games from the previous season to capture the long-term effect of wins, Pop_{it} is the market size measured by the population in the metropolitan area where the team located, Cap_{it} is stadium capacity, $Playoff_{it}$ is a dummy variable for postseason appearance, $Champion_{it}$ is the dummy variable for winning the championship in that season, and $Year_i$ is the dummies for years in the sample capturing the inflation and industry growth (2005 is the base year). The regression output is in Table 3.

About 58% of the variation in team total revenue can be explained by the model. Most of the explanatory variables are statistically significant. Market size and stadium capacity both have positive influence on total revenue. Being in the playoff does not affect team revenue. Team performance does have a positive impact on team revenue across both current and the immediate following seasons.

The marginal effect of Win82 on team revenue from the previous season is even more valuable as that of the current season. The present value of the expected return calculated from

$$\frac{\partial(TR)}{\partial(Win82)} = 486,640 + \frac{583,242}{1 + \delta}$$

where δ is the discount rate. Assume that the discount rate is 5%, an extra win generates \$1,042,109 to the team per season.

Is There a Winner's Curse in the NBA Players Market?

To discover the winner's curse, previous studies usually compare player's MRP to his salary. If salary exceeds MRP, they conclude that the winner's curse exists. For NBA players, the MRPs can be calculated by multiplying WS with MWV of \$1,042,109. Using a one-sided paired *t*-test for the null hypothesis that salary is equal to MRP against the alternative hypotheses that salary is smaller and greater than MRP, respectively, we reject the null hypothesis that salary is equal to MRP, but rather is greater than MRP ($p = 0.0000$); but cannot reject the null hypothesis that salary is equal to MRP when the alternative hypothesis states that salary is less than MRP ($p = 1.0000$). As a result, using salary-MRP comparison, the conclusion follows previous literature that the winner's curse does exist in the free-agent NBA players market.

Consider the cost-revenue of WS by comparing the marginal cost and marginal revenue, the conclusion is different. The marginal cost of WS is the amount of money teams spend to acquire an extra win generated by players. It is the same as the marginal effect of WS on player's salary. The marginal revenue is the return in dollar term a team

would earn if they win one more game in the season. It is the marginal effect of Win82 on team's total revenue, which is calculated to be \$1,042,109 per win.

The estimated coefficient of WS from the regression is tested against a null hypothesis that $\beta_{WS} \leq 1,042,109$. At the 5% level, we fail to reject the null hypothesis ($p = 1.0000$). As a result, teams, on average, spend less than what they get from an extra win. In other words, teams actually realized the true value of players and can eventually exercise their monopsony power to lower the salary below players' actual value.

Since teams determine salaries by including the uncertainty component, namely variance of WS into consideration, one should not draw any conclusion about winner's curse without taking into consideration this factor. The median of variance of WS is 8.79 means that, for an average player with regular variance in performance, the winner's curse occurs if $\beta_{WS} + 8.79\beta_{VarWS} > 1,042,109$. At the 5% level, the single tail t -test for the null hypothesis that $\beta_{WS} + 8.79\beta_{VarWS} \leq 1,042,109$ fails to reject the null hypothesis ($p = 0.9550$). Again, with the inclusion of uncertainty variable, there is still no evidence that teams are victims of the winner's curse.

An average star player receives \$8,748,409 as a premium while the 5.65 extra wins generated by an average star player provide his team $1,042,109 \times 5.65 = \$5,887,916$. One might conclude that the winner's curse does exist here. However, star players normally not only generate revenue to his team only through extra wins created. Autographs, souvenirs, jerseys, and so forth. of star players can create more money to the team. Due to the lack of detailed information about team revenue, this part of income cannot be estimated.

However, it is likely that another 42% of the revenue which cannot be explained by

marginal revenue model in this study will include star player indirect revenue. With this in mind, the winner's curse has less probability to occur under this circumstance.

The two findings are in conflict. Comparing only MRP and salary, teams fall in the winner's curse trap. However, it might not be reasonable to conclude that teams overestimate the value of players since another evidence suggests that they actually realize the true value and even pay players less than they should. The reason that salaries are greater than expected benefit of players can be because of other nonperformance player's characteristics and negotiation from the player union. Berri, Leeds, and von Allmen (2015) present that players are paid for something else besides wins, namely bargaining power. This power comes from the player union that has been successfully negotiating over team's fixed revenues such as those from broadcasting rights, a portion that is not included in the revenue function. The estimated bargaining power is computed by subtracting player's average salary by estimated MRP. In this study, the estimated bargaining power of free-agent players is \$2,938,109, less than the estimation of \$3,877,737 by Berri et al. (2015).

Berri et al. (2015) argue that the bargaining power equalized salaries with MRP. In this study, although the estimated bargaining power is almost 50% smaller than what was presented in Berri et al. (2015), the effect of the labor union and its bargaining power seems to be greater beyond just equalizing salaries to MRP. Instead, it raises salaries above MRP. This might sound illogical that team owners would allow this to happen. However, consider that players do not only create revenue through wins. Star players can bring more fans to the stadium. Their numbers on the jersey, their signatures, their photographs, and so forth, can be sold as team merchandise. These also generate dollars to team. As a result, the real bargaining power should be even less than the figure estimated.

It is also possible that the estimated bargaining power of the free agents comes from exploitation of wins generated by the nonfree agent players. Many players in the roster have less than 6 years of experience and are bonded with contracts that are usually compensated at the minimum wage. As of the 2015/16 season, a rookie's minimum salary is \$525,093 and the minimum salary for a player with 5 years of experience is \$1,100,602. If a player generates only 1 win to his team, his value should at least be \$1,268,327 if teams set wages equal to his MRP. The average nonstar player in this study is \$5,932,277. Considering this possibility, a part of the extra pay players receive as free agents is to compensate the exploited salary when they were not free agents. This lowers the dollar gains from bargaining power even further.

There are other costs necessary to generate wins beside payrolls such as managerial expenses, stadium maintenance costs, and so forth. As a result, the estimated MC of wins might be too low. However, this part of the cost is beyond the responsibility of players; although, teams could pass these costs onto players and lower their pays.

Conclusion

This study examines the market for free-agent NBA players whether there is a winner's curse problem or not. The characteristics of NBA free-agent player market deem appropriate for the study of the winner's curse. Previous studies on the winner's curse in major sports industry often compare salaries with MRPs. Most conclude that salary is greater than MRP, and hence, the winner's curse exists.

In labor economics, it is assumed that wage is equal to marginal cost of labor and that a firm will maximize benefit by equalizing marginal cost to marginal revenue product of labor. While the latter part of this assumption is still theoretically correct, in the real

world, the former part is not applicable as wages are normally determined by many factors. This study argues that salaries of NBA players are not solely determined by performance, but also other players' characteristics. As a result, it is not appropriate to directly compare salary with MRP, which is only estimated from the player's performance. Instead, the comparison between marginal cost and marginal revenue of win is applied.

Using the traditional method of salary-MRP comparison, it follows previous literature that the winner's curse exists. However, using the MC-MR comparison, this study discovers that teams indeed reward players less than the revenue they generated to teams, even after include the tendency for winner's curse such as the returns to variance of performance. Although there is no clear evidence, it seems likely that it is the same for star players. The winner's curse theory indicates that the winner of the bidding war "overestimated" the true value of product. As evidence presented in this study suggests, there is no evidence of such overestimation. Hence, this study concludes that there is no winner's curse problem in the bids for NBA free-agent players.

There still exists a positive difference between salary and MRP. One possible reason is that a part of the salary is determined by other players' characteristics that do not directly contribute to wins, such as age, experience, height, super star status, and so forth. Another possible factor is the bargaining power over team's fixed revenue, for example, TV broadcasting right income, that is, by agreement of the league and the NBA labor union, shared between teams and players. The extra wage above MRP can be a form of compensation that teams provide to players for a lower-than-MRP salary paid when players are not yet free agents. Teams could also pass other costs necessary to generate wins besides players such as managerial cost onto players and lower their wages.

Despite seemingly not being the cause of the winner's curse, star players are exploited from their contributions. The better performance of the star players, the more exploitation persists. This contradicts the economics of superstars theory by Rosen (1981), that return on performance increases in a nonlinear fashion. Future research can focus on the discovery of the relationship between player's characteristics to wins or performance, that has always been assumed to be constants. This will enable the possibility of monetary evaluation of player's characteristics that helps improve the precision of the estimation for player's marginal revenue product besides just from performance. It could, in turn, yield a more precise conclusion about the winner's curse through a more accurate expectation of benefit teams would have gained from players, since not every position requires the same type of player.

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Table 1: *Summaries of statistics from the 2004/05 to 2014/15 NBA Seasons*

Variables	Obs.	Mean	Std. Dev.	Min	Max
<i>Individual</i>					
Salary (\$)	691	6,741,807	4,929,465	304,897	23,239,562
Win Score (games)	691	3.65	3.94	-3.33	23.65
Variance of WS (games)	691	8.79	10.86	0.00	76.14
Height (in.)	691	78.64	3.69	65	87
Weight (lb)	691	216.13	27.33	135	325
Experience (year)	691	8.56	2.62	6	18
Age (year)	691	30.02	3.02	24	40
All Star	50				
Position, center	115				
Position, power forward	111				
Position, point guard	136				
Position, small forward	127				
Position, shooting guard	124				
<i>Team</i>					
Total Revenue	330	13,200,000	40,000,000	54,000,000	307,000,000
Team Payroll	330	66,738,678	12,562,757	23,380,124	126,610,272
Win82	330	40.99	12.66	9	67
Population	330	5,347,834	4,847,263	987,535	20,182,305
Stadium Capacity	330	19,103.430	1,046.442	16,867	21,165
Playoff	330	0.533	0.500	0	1

Table 2: *Regression of salary with robust standard errors*

Variable	Coef.	Std.Err.	<i>t</i>	<i>p</i> > <i>t</i>
Win Score	236,314.77***	54,626.18	4.33	0.00
Variance of Win Score	51,626.88**	20,885.17	2.47	0.01
Win Score × Star	-403,608.18***	135,941.31	-2.97	0.00
Age	967,098.58	811,076.98	1.19	0.23
Age ²	-27,940.96**	13,737.09	-2.03	0.04
Experience	682,977.51***	146,176.40	4.67	0.00
Height	231,392.35**	91,257.41	2.54	0.01
Weight	18,639.30	12,446.69	1.50	0.13
Dummy, star	9,693,614.43***	1,200,673.88	8.07	0.00
Dummy, center	-2,215,828.92**	1,052,580.50	-2.11	0.04
Dummy, power forward	-1,520,160.86	925,184.45	-1.64	0.10
Dummy, small forward	-795,136.81	708,917.63	-1.12	0.26
Dummy, shooting guard	43,710.89	553,666.29	0.08	0.94
Constant	-25,727,118.36*	14848176.30	-1.73	0.08
<i>R</i> ²	0.4535			
<i>Observations</i>	691			

Table 3: Regression of total revenue with robust standard errors

Variable	Coef.	Std.Err.	<i>t</i>	<i>p</i> > <i>t</i>
Win82 _{<i>t</i>}	486,639.74**	207,166.45	2.35	0.02
Win82 _{<i>t</i>-1}	583,242.03***	121,586.33	4.80	0.00
Market Size	3.90***	0.61	6.40	0.00
Stadium capacity	4,944.86***	1,121.24	4.41	0.00
Dummy, playoff	959,399.98	4,858,958.04	0.20	0.84
Dummy, champion	15,825,753.89***	4,596,913.50	3.44	0.00
Dummy, 2015	61485814.93***	8,377,452.17	7.34	0.00
Dummy, 2014	51,790,882.02***	6,582,970.97	7.87	0.00
Dummy, 2013	44,244,788.11***	7,048,305.76	6.28	0.00
Dummy, 2012	15,216,538.08***	5,888,741.08	2.58	0.01
Dummy, 2011	24,573,270.88***	5,939,553.02	4.14	0.00
Dummy, 2010	19,850,993.00***	5,814,125.03	3.41	0.00
Dummy, 2009	19,204,125.18**	5,911,644.16	3.25	0.00
Dummy, 2008	18,612,060.54**	5,827,442.17	3.19	0.00
Dummy, 2007	12,427,629.88**	5,878,378.59	2.11	0.04
Dummy, 2006	5,834,063.22	5,741,423.71	1.02	0.31
Constant	-53,074,811.83**	22,471,120.37	-2.36	0.02
<i>R</i> ²	0.5799			
Observations	329			

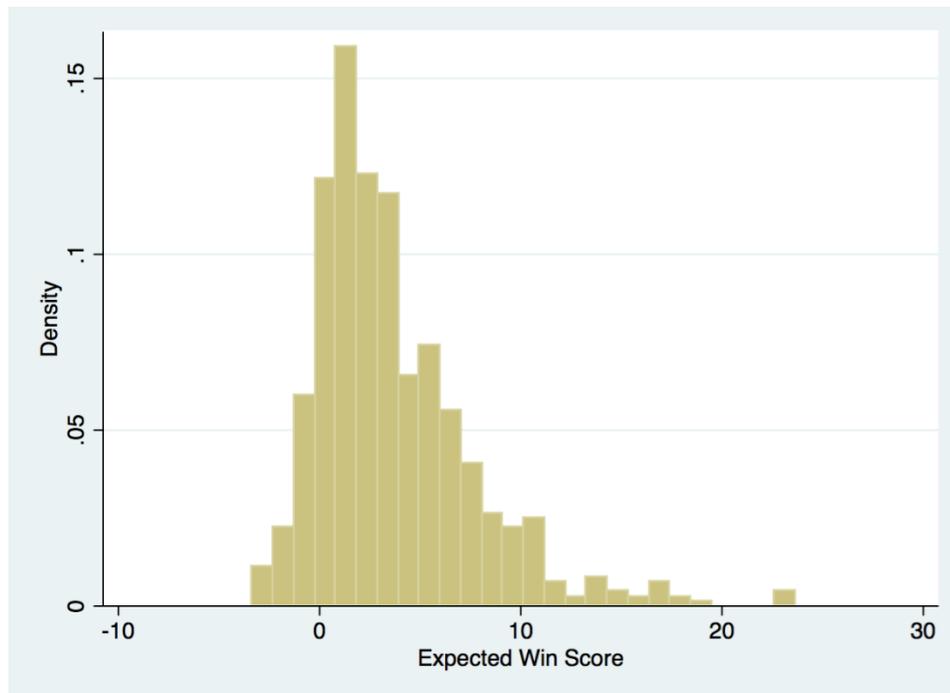


Figure 1: Histogram of free-agent players' expected win score

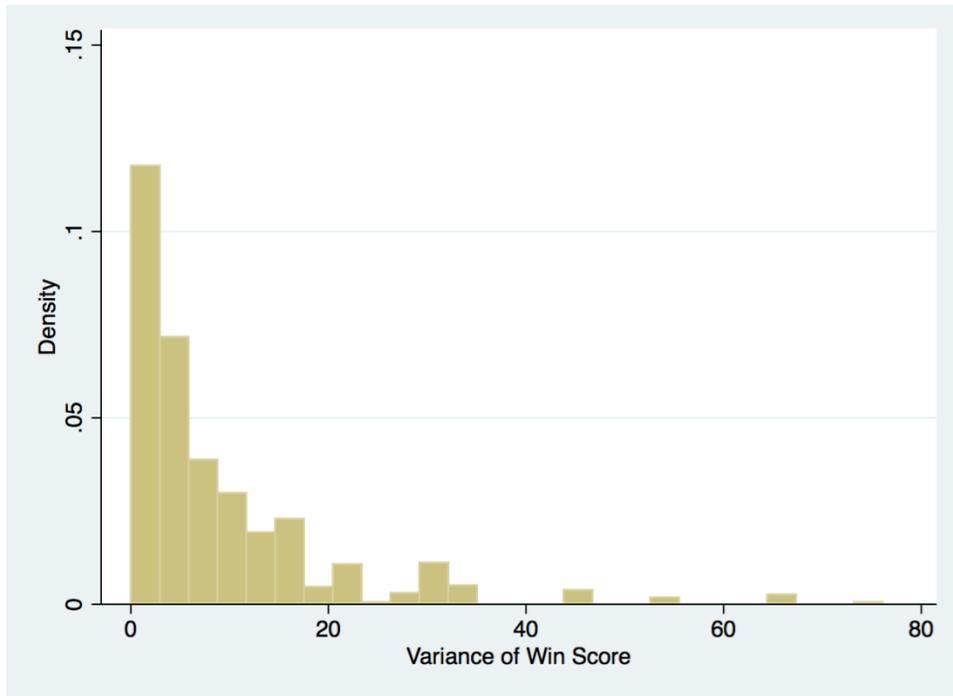


Figure 2: *Histogram of variance of free-agent players' expected win score*

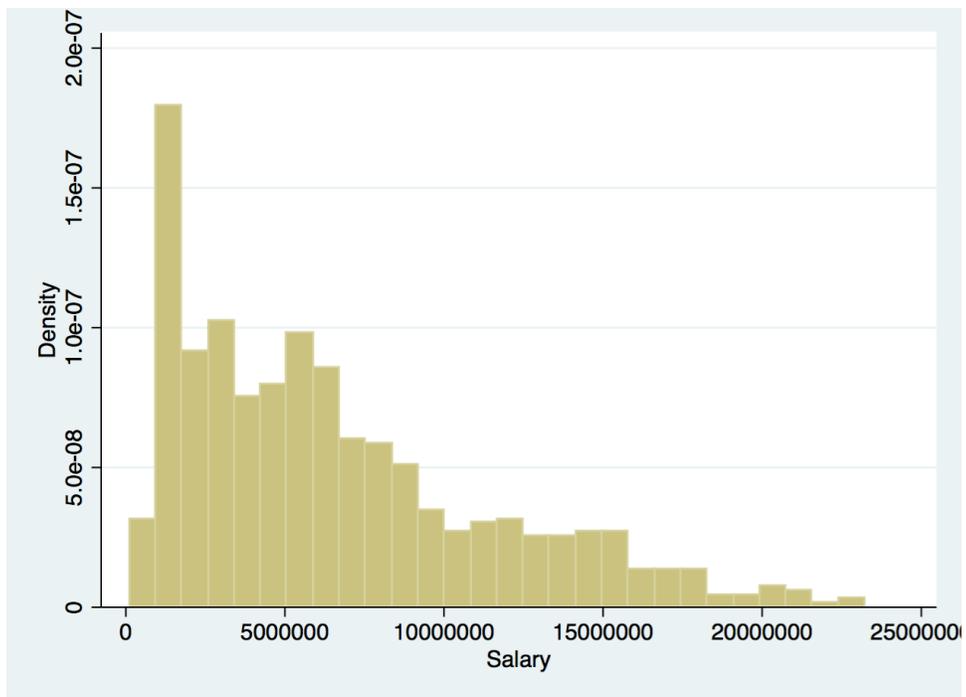


Figure 3: *Histogram of free-agent players' salary*