WAR: A PREDICTOR OF MLB TEAM'S SALARY AND SUCCESS

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ABSTRACT

This research explores the differences between two Wins Above Replacement (WAR) metrics as predictors of the expected baseball team salaries and overall team win percentage. The two different metrics calculate a different value for an individual player's WAR score, which is used to evaluate a player's total contribution to their team's success. Utilizing data from 1996 through 2015 from a popular baseball database, simple regression model results indicate that both the bWAR from Baseball-reference.com and fWAR from FanGraphs.com metrics significantly predict both team salaries and team performance. The research found that the fWAR metric was a better predictor of team performance.

INTRODUCTION

Major League Baseball (MLB) teams are always vying for a competitive advantage based on the combination of individual players on their payroll. In order to do so MLB team managers are seeking ways to spend money wisely on recruiting best players that will provide high chances of winning games on a tight budget. The more games a team wins, the better chance they have at qualifying for playoffs – a stepwise tournament that eventually determines the champion of the league. In order to evaluate individual player's overall contribution to the team, statistics are used to predict how well a player will perform, and in turn, how many wins a team can expect in a given season by utilizing such players in the team. Individual player's performance is evaluated using Baseball Sabermetrics, which is an empirical analysis of baseball statistics that measures players' in-game activity (Costa, Huber, & Saccoman, 2008).

Team managements have been under pressure to form the best possible sports teams. They seek to form successful teams while minimizing the total team players costs and they are increasingly turning to the field of analytics strategically select the best possible combination of good players that are affordable (Lewis, 2003). The approach of utilizing individual player's statistics as a way of evaluating players has defined a new culture. Major league baseball teams have followed suit by ramping up their advance scouting departments to evaluate players for draft and trade (Keener, 2014). In these departments, various metrics and statistics are analyzed to ensure that a team receives the highest value for its best players on the field, thus ensuring the highest chances at success (Koning & Albert, 2007). One such metric, Wins Above Replacement (WAR) explains how much better a player is in regards to statistically measured accumulated individual wins versus a minor league equivalent if that player had been playing on the major league team instead of the minor league team (www.baseball-reference.com/about/war_explained.shtml; www.fangraphs.com/library/misc/war/). Individual performances enhance or detract from the team's WAR depending on how successful a player is at batting, fielding, and/or pitching. All these aspects of play are taken into account when it comes to calculating the WAR metric. Players accumulate their own individual WAR scores, which indicate their personal contribution to the team's WAR score. In this paper, the team's WAR score is defined as the summation of the WAR scores of all individual players playing for the team.

Statistics and metrics used in management practices within the MLB have changed the landscape of the game over the past fifteen years (Schumaker, Solieman, & Chen, 2010). While each individual franchise has its own philosophy on the best use of salary spendings, this paper explores whether the WAR metrics are valid measures that can be utilized to determine whether salary dollars have a direct effect on overall team performance and team success (Schumaker et al., 2010).

Two professional baseball organizations measure the WAR metric in different ways. Baseball-reference.com uses bWAR while FanGraphs.com utilizes fWAR. Each of these organizations compile various factors that dictate their WAR score. These factors are used to project the number of wins by a particular team (www.baseball-reference.com/about/war_explained_comparison.shtml). Additionally, when teams trade for a different player with a higher WAR score, these individual WAR metrics can be used to evaluate potential improvements to the overall team performance.

WAR metrics have not been used to predict either team wins or team salaries in any sport management practice. Precisely predicting team salaries is important for developing an accurate budget for the season. Also correctly predicting the team percent wins is equally important, as that can determine the team's chances of winning the title. Since the WAR metric tracks individual player's performance statistics and could be used as an indicator of overall team performance, it may serve as a good predictor of team salaries and overall team winning percentage. This short overview leads to the following two research questions:

RQ1: Which of the two performance metrics (i.e. bWAR and fWAR) used to assess individual team player's performance is a better predictor of the overall team salaries.

RQ2: Which of the two performance metrics (i.e., bWAR and fWAR) used to assess individual team player's performance better explains the overall team winning percentage.

The rest of the paper is organized as follows: Next section provides a brief review of the literature on the WAR metrics. This is followed by the section that briefly explains the model and data collection techniques. The results are presented in next subsequent section, while the last section discusses conclusions and directions for future research.

LITERATURE REVIEW

The following literature review explores the ideas of predicting overall expected team performance along with causality between player compensation and performance. One of the most popular models for predicting overall team success in practical use is the Pythagorean Win-Loss Formula (Dayaratna & Miller, 2012; Miller, 2007), which has been derived from James's (1983) original model for predicting team success based on runs scored compared to runs allowed in a season. Luo and Miller (2014) revisited the model with the inclusion of a linear Weibull distribution to improve the predictability of team success. Bukiet, Harold, and Palacios (1997) explored a Markov Chain approach to run production based on outcomes for players of different abilities. Koop (2002) performed a similar study that considered offensive production output based on the number of times a batter was able to reach base by hit or walk.

A number of studies have utilized expectancy theory and player compensation, only focusing on "non-pitchers" (Ahlstrom, Si, & Kennelly, 1999; Duchon & Jago, 1981; Martin, Eggleston, Seymour, & Lecrom, 2011). Dinerstein (2007) offered insight on how often MLB players should be compensated, suggesting annual compensation to ensure that the teams are getting their best value by opting for individual players. Kleinbard (2014) explained that money spent on salaries in professional baseball is not the most valuable factor for team success and concluded that the Win Buying Index explains some of the variability in team salary. Hall, Szymanski, and Zimbalist (2002) tested the causality between team salary and team win percentage in both English Soccer and MLB. They found no statistical significance between team spending relative to the average team salary over a fifteen-year time span (1980-1994), but did observe high causality for one season in 1995. This study in particular has spurred intellectual curiosity that salary may be correlated to team winning percentage.

RESEARCH METHODOLOGY

It is important to accurately predict team salaries for a given season as that may help the management to generate an accurate budget. An accurate budget can help the management to control various resources better, communicate decisions across management levels, evaluate performance of players, and provide more visibility into team's overall performances. Team budgets can run in millions of dollars and a small deviation from the estimated budget could have a profound impact on the overall budget.

Another factor that is important for the team management is to have a high team win percentage. If MLB teams win more games, they may have a better chance at the playoffs. Winning more games may also help improve the team's overall performance ratings across all metrics, and allow players to demand higher salaries. This may also help the teams in attracting superior players that may further strengthen the teams' competitive position. fWAR and bWAR are two competing metrics that have been used historically to judge team performances. fWAR and bWAR metrics are to a certain extent similar, yet very different from each other when it comes to the various parameters that go into them to formulate the score. They are both composed of pitching and batting scores. These scores take into account the fielding statistics. This research specifically explores which of these two metrics is a better predictor of team salaries and team percent wins (Martin, 2016). To address these research objectives, simple regression technique is used with team salaries and team percent wins as dependent variables (DVs), and fWAR and bWAR metrics as independent variables (IVs).

This study utilizes data from *Lahman's Baseball Database* (http://www.seanlahman.com/), which collects a variety of historical data throughout MLB history. This study utilizes data from 1996 to 2015 MLB seasons, producing 596 individual team season records. The study utilizes both bWAR and fWAR scores for individual teams. Due to the twenty-season span of data, this study standardizes the team salaries for each season to ensure fair comparisons between team salaries across all the seasons over time. Standard team salary is calculated for each season "i" by utilizing the following formula:

$$\frac{TEAMSALARY_i - \mu(TEAMSALARY_i)}{\sigma(TEAMSALARY_i)}$$

Using standardized salary as the DV, the study performs two separate simple linear regressions using bWAR and fWAR scores as IVs. This may help us understand as to which of the two metrics explains more variation in the standardized team salary in a statistically significant way.

For the second research question, the study examines whether there is a difference in predicting the team win percentage based on the team fWAR and bWAR team scores. Since these two metrics tend to use different values based on the factors they possess, the study seeks to explore which of the two metrics is a better predictor of the actual team wins. This is important because the team management can form a team with either fWAR or bWAR score to ensure the type of outcome they believe is needed to be successful as a team. Further, we perform two separate simple regressions with team percentage win as DV and both fWAR and bWAR scores as IVs.

RESULTS

As stated in the above section, this study aims to explore if there is a difference in predicting team salary using fWAR and bWAR scores. The study first standardizes the team salary followed by two separate simple linear regressions to test the relationship between different WAR metrics and standardized team salary. The results for simple regression using the fWAR metric as an explanatory variable and standardized team salary as a DV are presented in Table 1. The regression model indicates a significant relationship between fWAR and standardized team salary. It is interesting to note that the adjusted r-square value is 0.154, which indicates that fWAR score explains about 15.4% of the variation in the standardized team salary.

The overall regression equation is given as follows:

$$STDSalary = -1.253 + 0.038fWAR$$

The regression equation shows the extent to which the salary deviates from the mean standardized salary per unit change in fWAR score. As can be seen from the above regression equation, the regression coefficient is 0.038. Although the regression coefficient is small, the impact on the overall team salary can be quite substantial as the team salaries are specified in millions of dollars.

TABLE 1: USING FWAR TO PREDICT TEAM SALARY

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.394[a]	.155	.154	.920673409141781

a. Predictors: (Constant), Total fWAR

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	92.502	1	92.502	109.129	.000[b]
	Residual	503.498	594	.848		
	Total	596.000	595			

a. DV: STD Salary

b. Predictors: (Constant), Total fWAR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.253	.126		-9.966	.000
	Total fWAR	.038	.004	.394	10.446	.000

a. DV: STD Salary

Next, simple regression is performed with the bWAR metric as an IV and standardized team salary as a DV. The results are presented in Table 2. The results indicate that the overall regression model is found to be significant. The adjusted r-square is found to be 0.122, indicating that bWAR score explains about 12.2% of the variation in standardized team salary. The regression equation observed is as follows:

$$STDSalary = -0.977 + 0.03bWAR$$

TABLE 2: USING BWAR TO PREDICT TEAM SALARY

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.351[a]	.123	.122	.937962397699851

a. Predictors: (Constant), Total bWAR

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	73.415	1	73.415	83.447	.000[b]
	Residual	522.585	594	.880		
	Total	596.000	595			

a. DV: STD Salary
b. Predictors: (Constant), Total bWAR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.977	.114		-8.597	.000
	Total bWAR	.030	.003	.351	9.135	.000

a. DV: STD Salary

Since the r-square value for the fWAR is approximately 3% higher than that of bWAR, we conclude that fWAR is a better predictor of team salary. Although this deviation of 3% in the standardized team salary may sound small, it could account for large sums of money as team salaries are stated in millions of dollars. Such useful information may assist baseball general managers in generating more accurate budget for team salaries.

Next, the impact of bWAR and fWAR metrics on team win percentage is examined. Two separate simple linear regressions are performed with bWAR and fWAR variables as predictor variables and team win percentage as a response variable.

Table 3 presents the results for simple regression with bWAR as IV. The results show that the regression model is significant, and indicates a significant positive relationship between bWAR scores and team win percentages. The adjusted R-square is 0.575, which indicates that 57.5% of the variability in team percent wins by a particular team can be explained by the bWAR score. The regression equation is as follows:

$$WINPCT = 0.352 + 0.005bWAR$$

The regression equation shows that for each unit increase in the bWAR score, the team win percentage increases by 0.005%.

TABLE 3: USING BWAR TO PREDICT TEAM WIN PERCENTAGE

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.759[a]	.576	.575	.045881

a. Predictors: (Constant), Total bWAR

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.696	1	1.696	805.611	.000[b]
	Residual	1.250	594	.002		
	Total	2.946	595			

a. DV: WINPCT

b. Predictors: (Constant), Total bWAR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.352	.006		63.235	.000
	Total bWAR	.005	.000	.759	28.383	.000

a. Dependent Variable: WINPCT

Further, we perform a simple regression with fWAR score as a predictor variable and team win percentage as a DV. Table 4, which presents these results, shows that the overall regression model is significant, indicating a positive relationship between fWAR score and team win percentage. The adjusted R-square is found to be 0.685, which means 68.5% of the variability in the team win percentage can be explained by fWAR score. This constitutes an 11% higher variation explained compared to the regression model in which the bWAR score is used as the IV, suggesting that fWAR is a better metric in explaining the team success compared to the bWAR metric.

TABLE 4: USING FWAR TO PREDICT TEAM WIN PERCENTAGE

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.828[a]	.686	.685	.039471

a. Predictors: (Constant), Total fWAR

The regression equation used is:

$$WINPCT = 0.315 + 0.006fWAR$$

The regression equation shows that for each unit increase in fWAR score, the team percent wins go up by 0.006%.

Historically, a majority of the industry relied on bWAR statistic to measure the team success. This research however proved by employing a series of simple linear regression models that the fWAR statistic is a better predictor of team success as it explained much more variation in comparison with the bWAR statistic. From a holistic standpoint, this can help team management to put together a better team that has higher chances of winning games. This can positively affect the team budget and help demand a higher overall team salary, and in particular a higher player salary.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.021	1	2.021	1297.107	.000[b]
	Residual	.925	594	.002		
	Total	2.946	595			

a. DV: PCT

b. Predictors: (Constant), Total fWAR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.315	.005		58.397	.000
	Total fWAR	.006	.000	.828	36.015	.000

a. Dependent Variable: WINPCT

CONCLUSION & FUTURE RESEARCH

The use of bWAR and fWAR metrics to predict team performance success have been helpful in forming a successful team to ensure overall team success. This can be valuable in decision making in sports management in terms of ensuring that roster or personnel changes are made strategically. This study finds that fWAR metric is a superior predictor of overall team salary and team percent wins compared to the bWAR metric as the fWAR metric explains comparatively more variation in the team salary and the percentage of games teams win.

Some of the limitations of this study include not accounting for any in-season trades or acquisitions made by teams while determining team salary. While such in-season players' trade-ins or acquisitions are taken into account in the team WAR calculations, salary restraints make it difficult to distinguish which team paid the player's salary, which makes it difficult to accurately evaluate the team salary. The performance of the traded player is calculated for their tenure with each individual team. Another limitation of this study is that the salaries are available for players who are active at the beginning of the season, which may vary due to outright release or injuries. This is not taken into account in the current study.

Future research may explore the factors that constitute the fWAR and bWAR scores in more detail. This could help understand which particular factors in fWAR score make it a better predictor of team success compared to bWAR score. Each metric includes similar yet different aspects, which could attribute to the variability in their values. Future studies may also explore the relationship between individual players' level of contribution to the overall team's success compared to the salary they are receiving. This may help the management in strategic decision making in the process of player selection, and could help ensure better alignment between teams' success and players' salaries. While these measurements were a summative value of teams' success, the reasons for winning an individual game may not be due to statistical success, but rather an incidental occurrence. Furthermore, bWAR and fWAR have become an accurate predictor of how well a baseball team will perform in a given season, and its accuracy can be utilized to determine to a very high degree of success on the field.

REFERENCES

Ahlstrom, D., Si, S., & Kennelly, J. (1999). Free-Agent performance in major league baseball: Do teams get what they expect? *Journal of Sport Management*, *13*, 181-96.

Baseball statistics and analysis. (n.d.). Retrieved from http://www.fangraphs.com/.

Bukiet, B., Harold, E. R., & Palacios, J. L. (1997). A Markov chain approach to baseball. *Operations Research*, *45*(1), 14-23.

Costa, G. B., Huber, M. R., & Saccoman, J. T. (2008). *Understanding sabermetrics: An introduction to the science of baseball statistics.* Jefferson, NC: McFarland & Co.

Dayaratna, K., & Miller, S. J. (2012). First order approximations of the Pythagorean won-loss formula for predicting MLB Teams' winning percentages. Retrieved from http://arxiv.org/abs/1205.4750.pdf.

Dinerstein, M. (2007). *Free agency and contract options: how major league baseball teams value players* (Unpublished master's thesis). Stanford University, USA.

Duchon, D., & Jago, A. G. (1981). Equity and the performance of major league baseball players: An extension of Lord and Hohenfeld. *Journal of Applied Psychology*, *66*(6), 728-732.

Hall, S., Szymanski, S., & Zimbalist, A. S. (2002). testing causality between team performance and payroll: The cases of major league baseball and English soccer. *Journal of Sports Economics*, *3*(2), 149-168.

James, B. (1983). Baseball Abstract. Lawrence, KS: Author.

Keener, M. H. (2014). The Econometrics of baseball: A statistical investigation. *Research in Business and Economics Journal*, *9*.

Kleinbard, M. (2014). Can’t buy much love: Why money is not baseball's most valuable currency. Boston, MA: MIT Sloan Sports Analytics Conference.

Koning, R. H., & Albert, J. (2007). *Statistical thinking in sports*. Boca Raton, FL: Chapman & Hall/CRC.

Koop, G. (2002). Comparing the performance of baseball players. *Journal of the American Statistical Association, 97*(459), 710-720.

Lewis, M. (2003). *Moneyball: The art of winning an unfair game*. New York: W.W. Norton.

Luo, V. & Miller, S. J. (2014). *Reliving and readjusting Pythagoras* (Bachelor’s thesis). Williams College, Williamstown, MA, USA.

Martin, J. A., Eggleston, T. M., Seymour, V. A., & Lecrom, C. W. (2011). One-Hit wonders: A study of contract-year performance among impending free agents in major league baseball. *A Journal of Baseball History and Culture, 20*(1), 11-26.

Martin, L. (2016). *Sports performance measurement and analytics: The science of assessing performance, predicting future outcomes, interpreting statistical models, and evaluating the market value of athletes*. Old Tappan: Pearson Education.

Miller, S. J. (2007). A derivation of the Pythagorean won-loss formula in baseball. *CHANCE, 20*(1), 40-48.

MLB stats, standings, scores, history. (n.d.). Retrieved from http://Baseball-Reference.com

Schumaker, R. P., Solieman, O. K., & Chen, H. (2010). Sports knowledge management and data mining. *Annual Review of Information Science and Technology, 44*(1), 115-157.

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