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NBA player contribution to team success

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Abstract

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1. Introduction

The relationship between player performance and team success in professional sports has an extensive history of anecdotal and statistical interest both from dedicated fans and team management. Winning generates fan excitement that translates into revenue opportunities. Given the association between winning and revenue, team management maintains a substantial financial incentive to ensure judicious spending on players to improve team outcomes.

Henry Chadwick developed the box score for baseball in 1858 and the age of modern sports analytics was born (Pesca, 2009). The complementary relationship between statistics and baseball resulted in rapid adoption and proliferation of player performance assessment methods. Baseball is a team game, but the actions of individual players during the game are generally discreet and isolated. Independent play makes baseball conducive to statistical analysis. Player evaluation methods originated and evolved in baseball and eventually migrated to other sports. As player performance measures carried forward into other sports, however, the fit often suffered. Standard offensive measures are less relevant and inadequate in sports with higher degrees of interdependent play.

Basketball is a sport where play is dictated by player interaction and highly interdependent play. Team chemistry and collaboration are extremely important in achieving favorable outcomes. A player can make positive contributions while not being prolific in obtaining offensive statistics. The current emphasis on individual statistics potentially encourages player activity that is divergent from team interests since players are monetarily rewarded for accumulating offensive statistics, even if detrimental to team play. Focusing on these metrics' risks overvaluing players that fill a box score but provide little benefit to game outcome while ignoring the potential value of others. Team management can incorrectly value players leading to an inefficient allocation of payroll expenditures.

The paper estimates the isolated contribution of individual players to team success in the National Basketball Association (NBA) as a variant of the "plus/minus" statistic. Success is achieved by outscoring opponents, irrespective of individual statistics or method of player contribution. Players can be prolific scorers, assist teammates, be outstanding defenders, rebound, create steals, display outstanding hustle, and motivate teammates.

The study creates a novel method that assesses individual contributions to team success irrespective of individual achievement, while also controlling opponent quality and providing statistical significance. The plus/minus of the player is calculated for each event during the game rather than aggregated throughout the game. This allows for more detailed analysis. The coefficients of the player binaries are a metric that team management can be used to assess player performance to determine how much influence, positive and negative, the player has on team success. The method focuses solely on team success and assessing a player's efficiency in providing this outcome. By focusing on this metric rather than individual player statistics, management can allocate player expenditures more efficiently and help ensure more successful team outcomes.

2. Literature Review

Professional sports franchises derive profitability from many sources, including fan support which generates revenue from attendance, team merchandising, and broadcasting (Buraimo, 2008). As teams are driven to maximize profits, they desire winning teams to generate increased fan interest to drive greater revenues. Demmert (1973), Noll (1974), and Horowitz (1978, 2007) in seminal work establish the relationship between on-field success and fan interest. Whitney (1988) likewise finds winning, and the potential of postseason play increases fan excitement and attendance. While the link between team success and fan interest is well established, there are some notable caveats and exceptions. Davis (2008) finds the link to be fleeting and does not extend into future periods. Alternatively, Zimmer (2014, 2018) argues the link weakens at the extremes of team success. An abundance of team success desensitizes fans and reduces attendance. At the other extreme, long-suffering teams with little success are represented by loyal and active fan bases.

Large market franchises with more financial resources are inclined to outspend the smaller markets to acquire better talent. The NBA adopted a salary cap system to restrict large market team spending to increase the parity of play across the league. With team payrolls being limited and equalized, teams seek advantage with better player evaluation. Teams look to ascertain and acquire better players by finding ‘value’ within the pool of available player talent. Superior player evaluation can be a source of long-term competitive advantage.

NBA teams use quantitative data analysis to assess player performance. These efforts produce a litany of player statistics, some of which are publicly available while others likely remain proprietary. The “plus/minus” statistic is a prevalent measure used to assess the game impact of players. It is an attempt to directly link a player with team outcome. These models typically extract a suitable game dataset and apply a common regression procedure (Kubatko et. al., 2007; Oliver, 2004). The metric’s popularity has generated interest and numerous variants of refinement. In another common construction, a resulting weighted least squares (LS) problem produces coefficients known as the “adjusted plus/mis ratings”. In subsequent research, attempts are made to address deficiencies and offer alternative approaches which produce greater predictability (Omidiran, 2013). This study is consistent with prior research and incrementally expands existing lines of inquest.

3. Methodology

The 2023-2024 NBA regular season consists of 30 teams found on Table 1 each playing 82 games. Post-season play is not included. Teams play half the games at their home stadium while traveling for the remainder. A game is played with 5 players from each team competing at one time. Teams maintain a roster of approximately 15 players, but this varies over the season due to trades, short-term contracts, injuries, etc. The duration of a standard game is 48 minutes broken into 4 quarters of 12 minutes. The team with the most points at the end of regulation play wins. If the score is tied at the end of regulation play, additional allotments of 5-minute periods are played as overtime until a victor is determined.

Table 1

#	Team	#	Team
1	Atlanta Hawks	16	Miami Heat
2	Boston Celtics	17	Milwaukee Bucks
3	Brooklyn Nets	18	Minnesota Timberwolves
4	Charlotte Hornets	19	New Orleans Pelicans
5	Chicago Bulls	20	New York Knicks
6	Cleveland Cavaliers	21	Oklahoma City Thunder
7	Dallas Mavericks	22	Orlando Magic
8	Denver Nuggets	23	Philadelphia 76ers
9	Detroit Pistons	24	Phoenix Suns
10	Golden State Warriors	25	Portland Trail Blazers
11	Houston Rockets	26	Sacramento Kings
12	Indiana Pacers	27	San Antonio Spurs
13	Los Angeles Clippers	28	Toronto Raptors
14	Los Angeles Lakers	29	Utah Jazz
15	Memphis Grizzlies	30	Washington Wizards

Primary data are manually gathered while watching games as secondary sources conforming to the needs of the study were not identified. An approximately equal number of games were watched by each author and data manually collected. Given the complexity and time-consuming method of data collection, the study only examines one team, the Indiana Pacers. The use of unofficial primary data suggests the potential of minor variation from official data if they exist.

Current basketball strategy often involves finding advantageous matchups or player pairings. An opportunity exists if a player pairing with a mismatch of skill levels is identified. For example, a desirable circumstance for a team is when a player on offense is paired with a counterpart on defense with less skill, thus increasing the probability of obtaining points. Teams run set plays to force defensive switches to create advantageous pairings. Coaches make player substitutions to alter player groupings on the court to achieve optimal matchups. Therefore, each player grouping, 5 players for each team or 10 total players on the floor at a time, creates a distinct moment or event within the game. A game is the cumulation of these individual events. One event ends and another starts with a player substitution by either team or a substantial break in play that allows coaching. Breaks in play typically result from timeouts (team, official, or television) or intermissions at the end of quarters.

Events during the game are discrete observations and each generates a unique outcome, the event net score. A positive event net score indicates the Pacers scored more than the opponent during the event while a negative event net score indicates the opposite outcome. An event net score of zero indicates both teams scored equally during the event.

Current versions of plus/minus statistics calculate player value for the entire game, regardless of player combinations for either team. This novel approach calculates the value for each of the events during the game. Essentially each event is treated as an independent game and creates a unique plus/minus statistic for each player for that portion of the game. This ensures a significantly higher observation count and allows for regression analysis which is currently not possible with the standard plus/minus calculation.

A total of 2,923 events are observed for the Indiana Pacers during the 2023-2024 regular season. The Pacers use 22 players with a listing provided on Table 2. Players P1 to P17 are on the roster at the start of the season. Players P18 to P22 are added via trade or contract. During the season, 522 different 5-player combinations are utilized in games. Starters appear in more events than non-starters. Some players appear only sparingly.

Table 2

Player #	Player Name	Jersey #
P1	Bennedict Mathurin	00
P2	Tyresse Haliburton	0
P3	Obi Toppin	1
P4	Andrew Nembhard	2
P5	Jarace Walker	5
P6	Buddy Hield	7
P7	T.J. McConnell	9
P8	Kendall Brown	10
P9	Bruce Brown	11
P10	Jordan Nwora	13
P11	Isaiah Wong	21
P12	Isaiah Jackson	22
P13	Aaron Nesmith	23
P14	Jalen Smith	25
P15	Ben Sheppard	26
P16	Myles Turner	33
P17	Oscar Tshiebwe	44
P18	Daniel Theis	27
P19	James Johnson	16
P20	Pascal Siakam	43
P21	Doug MeDermott	20
P22	Quenton Jackson	29

Player binary variables are created. The variable is positive (1) if the player is one of the 5 players on the court for the event, negative (0) otherwise. To ensure sufficient observations and robust results, only players on the active roster at both the beginning and conclusion of the season are included in the analysis. Players are excluded due to season-ending injuries, trades, or mid-season acquisition activity. The inclusion criteria are matched by 13 players (*P2, P3, P4, P5, P7, P8, P11, P12, P13, P14, P15, P16, and P17*).

Events are measured in whole seconds with partial seconds rounded. To accommodate events of vastly unequal duration and diminish this influence on the results, the event net score is normalized to 60 seconds. The net score of each event is divided by the number of seconds of the event to establish a per second basis and then multiplied by 60 to ease understanding (*ENSperMin*).

Normalizing the event net score equalizes the outcome effect for events of varying duration. However, it may skew results for events of very short duration. At the end of a game, it is common for a team to call a timeout with a few seconds remaining to plan for the final possession. This denies the other team the possibility of possession and has the potential to bias results for players that are substituted in for offensive or defensive purposes. Short duration events may also influence results by overweighting their impact when normalizing to 60 seconds as it inflates net scores for these events. Therefore, data are sorted and grouped into normal duration events exceeding 24 seconds and short duration events of 24 seconds or less. The shock clock in the NBA for the 2023-2024 season is 24 seconds, so events longer than 24 seconds approximate an equal opportunity for possession for each team.

Control variables include a back-to-back binary (*BTB*). Due to league scheduling, teams infrequently play games on consecutive days. The binary is positive (1) if the game is the second of back-to-back games, or negative (0) otherwise. A binary variable for home games (*Home*) during the season is included. The variable is positive (1) for the 41 homes games and negative (0) otherwise. The final control variable (*Win*) is the winning percentage of the opposing team during the 2023-2024 regular season and is a proxy for opposing team quality. Summary statistics for all variables are provided on Table 3.

Table 3

Summary Statistics

	Dependent Variable	Notation	Obs.	Mean	Std. Dev.	Min.	Max.
1	Event Net Score Per Minute	$ENSperMin_{g,i}$	2,923	-0.012	6.615	-120	120
	Independent Variables	**Notation**	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
1	Back-to-Back Game Binary	BTB	2,923	0.163	0.370	0	1
2	Home Game Binary	Home	2,923	0.497	0.500	0	1
3	Opponent Win Percentage	Win	2,923	0.490	0.169	0.171	0.780
4	Player 2	P2	2,923	0.539	0.499	0	1
5	Player 3	P3	2,923	0.468	0.500	0	1
6	Player 4	P4	2,923	0.417	0.493	0	1
7	Player 5	P5	2,923	0.084	0.277	0	1
8	Player 7	P7	2,923	0.358	0.480	0	1
9	Player 8	P8	2,923	0.012	0.110	0	1
10	Player 11	P11	2,923	0.001	0.026	0	1
11	Player 12	P12	2,923	0.214	0.410	0	1
12	Player 13	P13	2,923	0.508	0.500	0	1
13	Player 14	P14	2,923	0.291	0.454	0	1
14	Player 15	P15	2,923	0.220	0.414	0	1
15	Player 16	P16	2,923	0.463	0.499	0	1
16	Player 17	P17	2,923	0.008	0.088	0	1

An ordinary least squares model is used, and the base model is equation 1. The dependent variable is event net score per minute (*ENSperMin*) for events in the 2023-2024 regular season. Independent variables include the back-to-back binary (*BTB*), home game binary (*Home*), opponent win percentage (*Win*), and the 13 player binaries (*P2, P3, P4, P5, P7, P8, P11, P12, P13, P14, P15, P16, and P17*).

$$
\begin{aligned}
ENSperMin_i = {} & \beta_0 + \beta_1(BTB_i) + \beta_2(Home_i) + \beta_3(Win_i) + \beta_4(P2_i) + \beta_5(P3_i) + \beta_6(P4_i) \\
& + \beta_7(P5_i) + \beta_8(P7_i) + \beta_9(P8_i) + \beta_{10}(P11_i) + \beta_{11}(P12_i) + \beta_{12}(P13_i) \\
& + \beta_{13}(P14_i) + \beta_{14}(P15_i) + \beta_{15}(P16_i) + \beta_{16}(P17_i) + \epsilon
\end{aligned} \tag{1}
$$

$$where\ i = event$$

Data are sorted into normal duration events exceeding 24 seconds, and short duration events of 24 seconds or less. The number of observations in the normal duration event group is 2,437 and the short duration event group is 486. The model is run on both groups. Statistical significance is more difficult to obtain in the short duration model due to fewer observations.

4. Results

Model results are on Table 4. The coefficient for the back-to-back binary (*BTB*) is negative and highly significant in both models. In both normal duration and short duration events, the fatigue of playing on consecutive days negatively influences player performance. The coefficient for the home game binary (*Home*) is positive in both models and significant in the normal duration model, indicating a home court benefit to player performance. The coefficient of the opponent win percentage (Win) is negative in both models and significant in the normal duration model. The results indicate that playing against better opponents, player performance declines.

Table 4

	Independent Variables	#1 Main Model Event > 24 seconds Net Score per Minute *(ENSperMin $_i$)* Coef.	S.E.	#2 Subset Model Event <=24 seconds Net Score per Minute *(ENSperMin $_i$)* Coef.	S.E.
1	BTB	-0.321 ***	0.160	-5.262 ****	1.877
2	Home	0.204 **	0.115	0.240	1.404
3	Win	-0.521 *	0.341	-3.739	4.162
4	P2 (Haliburton)	0.379 ****	0.143	-1.034	1.722
5	P3 (Toppin)	0.275 ***	0.138	-0.197	1.595
6	P4 (Nembhard)	0.182	0.145	-3.395 ***	1.663
7	P5 (Walker)	0.297 *	0.232	0.514	3.090
8	P7 (McConnell)	0.355 ***	0.167	-4.213 ***	1.926
9	P8 (Brown)	-0.147	0.560	-3.683	10.785
10	P11 (Wong)	-3.894 **	2.035	omitted	
11	P12 (Jackson)	0.072	0.220	0.976	2.265
12	P13 (Nesmith)	0.217 *	0.133	-2.198	1.602
13	P14 (Smith)	0.091	0.196	-1.034	2.076
14	P15 (Sheppard)	0.077	0.156	0.081	1.828
15	P16 (Turner)	0.135	0.204	2.890 *	2.078
16	P17 (Tshiebwe)	0.606	0.672	-2.531	10.905
	Intercept	-0.600		6.289	
		F (16 , 2420) = 1.63 *Prob > F 0.0539* *Observations 2,437*		*F (15, 470) = 1.45* *Prob > F 0.1193* *Observations 486*	

Significant: * at 20%, ** at 10%, *** at 5% , **** at 1%

The player binary variable coefficients assess a player's impact on team outcomes. The NBA is a star driven league with the over-weighting influence of the best players in determining game outcomes (Omidiran, 2013). The preponderance of NBA players possess a skill level near to the league average, resulting in a binary coefficient value approximating zero and an insignificant result. As all players in the NBA are well paid professions, the expectation is that even an average NBA is highly skilled. Players that can exceed the average are exceptionally rare. A positive and significant coefficient indicates an elite or star player. For this reason, levels of significance are broadened slightly to reflect the difficulty of athletes differentiating within the league.

The coefficient for the Player 2 (*P2*) variable is statistically very highly significant and positive in the normal duration event model. In normal duration events, Haliburton makes the largest contribution to team success and is the most statistically significant player finding. He contributes nearly 0.38 points for every minute played during normal duration events. His contribution during short duration events is not statistically significant.

The coefficient for the Player 3 (*P3*) variable is statistically highly significant and positive in the normal duration event model. In normal duration events, Toppin makes a positive contribution to team success. He contributes nearly 0.28 points for every minute played during normal duration events. His contribution during short duration events is not statistically significant.

The coefficient for the Player 4 (*P4*) variable is not statistically significant in the normal duration event model. In short duration events, the coefficient is statistically highly significant and negative. Nembhard costs nearly -3.40 points for every minute played during short duration events. As noted, this may be a function of offensive and defensive substitution patterns common during short duration events. Nembhard is often a defensive substitute which can result in a negative coefficient as there is no potential for a positive result.

The coefficient for the Player 5 (*P5*) variable is statistically significant and positive in the normal duration event model. In normal duration events, Walker makes a positive contribution to team success. He contributes nearly 0.30 points for every minute played during normal duration events. His contribution during short duration events is not statistically significant.

The coefficient for the Player 7 (*P7*) variable is statistically highly significant and positive in the normal duration event model. In normal duration events, McConnell makes a positive contribution to team success. He contributes nearly 0.35 points for every minute played during normal duration events. During short duration events, the coefficient is statistically highly significant and negative. McConnell costs nearly -4.20 points for every minute played during short duration events. As noted previously, this secondary finding may also be the result of offensive and defensive substitution patterns during short duration events. McConnell is often a defensive substitute which can result in a negative coefficient as there is no potential for a positive result.

The coefficient for the Player 11 (*P11*) variable is statistically highly significant and negative in the normal duration event model. In normal duration events, Wong makes a negative contribution to team success. He costs nearly 3.9 points for every minute played during normal duration events. His contribution during short duration events is not statistically significant. Wong never appeared in a short duration event, so this variable is omitted.

The coefficient for the Player 13 (*P13*) variable is statistically slightly significant and positive in the normal duration event model. In normal duration events, Nesmith makes a positive contribution to team success. He contributes nearly 0.22 points for every minute played during normal duration events. His contribution during short duration events is not statistically significant.

The coefficient for the Player 16 (*P16*) variable is not statistically significant in the normal duration event model. In the short duration of events, the coefficient is statistically slightly significant and positive. Turner contributes nearly 2.90 points for every minute played during short duration events. Turner is the only player to exhibit positive significance in short duration events, such as end of quarter/game scenarios, and is most valuable in these situations.

Players 8, 12, 14, 15, and 17 (*P8, P12, P14, P15, and P17)* are not shown to be statistically significant in either normal duration or short duration events.

Some players are younger and developing, with limited playing time. The lack of playing time and event observations may be a contributing factor to insignificant results. Additionally, as playing time may be rare, the instances in which such a player may appear are at the conclusion of noncompetitive games, potentially influencing results.

5. Discussion

NBA franchises desire to win games consistently as victories are a substantial driver of revenue and profitability. Management strives to assemble a cohesive team of complimentary talent to achieve success within the constraints of limited player expenditures stemming from league salary cap rules. Due to the financial self-interest of players, however, there may be an inherent misalignment between player and team objectives. The top priority from the player's perspective may be their compensation. Current trends in player evaluation and contract negotiations favor individual statistics. Acting rationally to enhance their financial prospects within this context, a player may work to accumulate individual statistics, even if detrimental to team outcome. The focus on individual statistics may result in overvaluing accumulated statistics that do not translate to team success.

Methods of enhanced player assessment, such as the 'plus/minus' statistic and its numerous derivatives, are positive advancements. However, they lack variable controls for the quality of an opponent or provide an indicator of estimate statistical significance. A quality player that spends a large portion of their court time against non-starters or playing against teams of lower quality may have an inflated plus/minus statistic. Likewise, a quality player may be undervalued if competing primarily against other higher quality players.

The results indicate with statistical significance that Haliburton and McConnell are the most valuable players for the Indiana Pacers during normal duration events. They contribute approximately 0.38 and 0.36 points respectively per minute played towards the Pacers outscoring an opponent. NeSmith, Toppin, and Walker also maintain a positive impact, though to a lesser degree and statistical significance. Other players on the team are comparable to the average NBA players, as indicated by contribution levels approaching zero and lack of statistical significance. Wong, a young player with limited playing time, has a negative contribution and statistical significance. In short-term events, Turner maintains a positive and statistically significant contribution. Turner's value is most apparent during short duration events such as end of quarter/game scenarios.

The approach can be enhanced with additional data. First, the analysis can be expanded to the entire league. A league-wide player assessment will assist management in assembling talent and become a source of long-term advantage. Ideally, value' players that achieve team success greater than their relative wage can be identified and targeted for acquisition. Second, the opponent control can be improved as the current iteration only assesses the quality of the entire team. Rather than using a single term for the entire team, the opponent control can be altered to reflect the skill of the opposing players on the court at the event level, allowing for player variation on opposing teams. Additionally, while not done in this preliminary analysis, further analysis can be conducted on the behavior of this plus/minus statistic on player groupings. As the statistics are calculated for each player grouping (5-player combinations), the plus/minus statistics of an individual player will vary based on teammate grouping. This could help determine which players play well together and generate the best chance of team success. Finally, a larger dataset may allow for the evaluation of innovative modeling techniques.

Many factors influence player evaluation that are outside the bounds of this study. The results only represent the timeframe included and do not forecast the future. Player performance varies over time, and contracts are frequently offered over multiple years. Coaches may decide that a younger player with upside potential requires additional playing time to maximize their ability. A developing player may warrant acquisition and playing time in excess of the current play contribution because of the potential represented. Likewise, a veteran player may be on the decline due to age, injury, or loss of focus. This analysis only examines the play within the period studied, with no consideration of the future skill progression or decline.

Another factor that influences player evaluation is team fit. The success of a player may not transfer from one team to another. A player's value on a new team might be significantly different (either positively or negatively) due to factors such as coaching, different schemes of play, or changes in the team chemistry on differing teams. These factors impact player evaluation but are beyond the scope of this study.

Finally, professional sports are entertainment. In some circumstances a player's popularity with the public may be incongruent with their skill. A player's ability to attract interest and revenue exceeds their capacity to achieve team victory. Acknowledging the marketing reality in these circumstances, the salary paid to such a player may be inconsistent with the quality of their play.

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