WINSCORE Revisited: A Model-Based Evaluation of Player Performance in the NBA and EuroLeague *

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Abstract

In professional basketball, player evaluation often relies on aggregated box-score statistics. The Performance Index Rating (PIR), widely used in leagues like the NBA and EuroLeague, lacks a clear statistical foundation and may not reliably reflect a player's contribution to team success. This paper revisits WINSCORE, an approach proposed by Berri et al. (2006), which links individual player statistics directly to team outcomes, offering a more interpretable and theoretically grounded measure of player value.

We reinterpret WINSCORE as a model-based procedure and validate its application in measuring team and player performance using data from both the NBA and EuroLeague. In doing so, we highlight its advantages over traditional metrics.

Finally, the model-based interpretation of WINSCORE allows to introduce a new modified WINSCORE-based method to evaluate player performance in individual games, illustrated with EuroLeague data. This extension provides a useful tool for coaches and analysts seeking game-level insights into player efficiency.

Keywords: Player Performance Evaluation, Basketball Analytics, EuroLeague, WINSCORE Model, Performance Index Rating (PIR)

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1 Introduction

As clearly illustrated by Page (2018) in his insightful book on model thinking, organizing and interpreting data through models has become a core competency across many domains, including business strategy, urban planning, economics, medicine, engineering, actuarial science and environmental science, among others. This paper adopts a model-based approach to reinterpret a performance indicator built on basketball data by optimally weighting several statistics.

In professional basketball, player evaluation is often based on aggregated box-score statistics,(Zhou and Li, 2024). The Performance Index Rating (PIR) remains the most widely used metric in top leagues such as the NBA and the EuroLeague. However, PIR lacks a clear statistical foundation and may not reliably capture a player's true contribution to team success. This paper demonstrates how the WINSCORE approach, proposed by Berri and Eschker (2005) and popularized by Berri et al. (2006), can be embedded within a model-based framework that directly links individual player statistics to team performance outcomes, yielding a more grounded and interpretable measure of player value.

The WINSCORE approach is based on the theory that the wins of a basketball team depend structurally on efficient possession management. The concept of possessions was introduced in the early work of Hollinger (2002) and Oliver (2004), where it is treated as the basic currency of the game: winning or losing hinges on the differential between points scored and points allowed per possession. This foundational idea is further developed in Berri and Eschker (2005) and Berri (2008), where a performance index is created by optimally weighting various box-score statistics.

A modeling approach grounded in the theory linking possessions to wins allows the data to inform the optimal weighting of statistics, leading to a single, interpretable indicator of player performance.

The remainder of the paper is structured as follows. The first section discusses the challenges of collinearity and identification that arise when aggregating statistics, using NBA and EuroLeague box-score data as references. We also highlight the presence of a common structure in these data. The second section reviews the popular PIR metric and demonstrates its main limitations. The third section outlines the workings of the model-based approach, detailing the steps of specification, estimation, validation, and simulation. The fourth section shows how the WINSCORE method fits within the model-based framework, applying all the steps to EuroLeague data to generate optimal weights for player statistics. The fifth section interprets the resulting model, enabling the construction of new efficiency indicators for players. These are implemented in the sixth and seventh sections, using regular season and single-game data, respectively. The final section concludes.

2 Wins and Box-Score Statistics: Data-analysis Without a Theory

Leagues like the NBA and the Euroleague make Box-Score statistics available online for the different seasons t, the different teams i, and the different players j, for each team all available statistics are matched by the opponent statistics.[1] The following statistics are available:

- Field Goals (FG): Number of field goals made.
- Field Goal Attempts (FGA): Number of field goal attempts.
- Three-Point Field Goals (3P): Number of three-point shots made.
- Three-Point Attempts (3PA): Number of three-point shots attempted.
- Free Throws (FT): Number of free throws made.
- Free Throw Attempts (FTA): Number of free throw attempts.
- Offensive Rebounds (ORB): Number of offensive rebounds secured.
- Defensive Rebounds (DRB): Number of defensive rebounds secured.
- Assists (AST): Number of assists made.
- Steals (STL): Number of steals.
- Blocks (BLK): Number of shots blocked.
- Turnovers (TOV): Number of turnovers committed.
- Personal Fouls (PF): Number of personal fouls. In addition to PF the Euroleague makes Fouls Drawn (FD) available.

The research question relevant here is how these data can be used to build a single measure of efficiency that can be associated to each player to measure productivity? In this section we consider the construction of measures without theory, by analysing first the PIR approach and by then assessing the difficulties in using simple correlation analysis.

[1] *https://www.euroleaguebasketball.net/en/euroleague/* allows to retrieve real-time and historical standard and advanced statistics about competitions, teams, players and for the Euroleague. The same stats for the NBA can be retrieved from *https://www.basketball-reference.com/*. The Data appendix provides a detailed description of the data we have used in this study.

2.1 The PIR approach

The Performance Index Rating (PIR) is a statistical formula used in basketball to evaluate a player's overall performance. It simply aggregates various positive statistics such as points, assists, rebounds, blocks, and steals, while subtracting negative actions like turnovers and missed shots.

$$
\begin{aligned}
PIR &= PTS + REB + AST + STL + BLK + FD \\
&\quad - FGMISS - FTMISS - TOV - PF
\end{aligned}
$$

The PIR is made available for the NBA for each team and players. In Europe the approach was originally developed by the Spanish ACB League in 1991, and it has been then adopted by major European competitions, including the EuroLeague, to determine weekly MVPs and assess player contributions. The press and sports commentators often utilize PIR to highlight standout performances and compare players across different games and seasons. Agents also reference PIR when negotiating contracts, as it provides a quantifiable measure of a player's impact on the court (Wen et al., 2023).

However, coaches have expressed reservations about relying solely on PIR for player evaluation. According to the World Association of Basketball Coaches [2], while official game statistics like PIR offer valuable insights, they may not fully capture a player's effectiveness or contribution to team dynamics.

Coaches' reservations about PIR are well-founded. The metric aggregates positive and negative stats without assigning them appropriate weights. For instance, a missed free throw and a missed field goal—which can cost the team two or three points—are treated equally, despite their different opportunity costs. Similarly, an assist, which directly contributes to scoring and it is therefore worth at least two points, is valued the same as a missed free throw. Moreover, PIR does not account for opponent statistics or the game's final outcome. Intuitively, a player's performance should be evaluated relative to their opponent's performance and weighted by its impact on the game's result.

2.2 Can Measurement Without Theory Help ?

Given that each game result is important, what are the difficulties of using theory-free measures of the relationship between statistics and game results to weight them ? Consider the simplest measure of linear relationships about statistical variables, namely correlation, and apply correlation analysis to wins and statistics reported in the box-score. We report in

[2] $https://about.fiba.basketball/en/organization/recognized-organizations/world-association-of-basketball-coaches$

Figures 1-3 the correlation between win percentages and box score stats for the Euroleague on a post-COVID sample and for NBA data from two different samples, a post-COVID sample and an earlier sample covering seasons from 1992-1993 to 2004-2005. The evidence highlights the limitations of relying on simple correlations between win percentages and box-score statistics to evaluate team performance. For example, offensive rebounds exhibit a negative correlation with the percentage of wins. Interpreting this at face value and assigning a negative weight to offensive rebounds in a composite performance metric would be misleading. This is because offensive rebounds are highly correlated with missed field goals, which themselves are negatively associated with winning. Thus, offensive rebounds act as a proxy for poor shooting rather than being intrinsically detrimental. Despite these pitfalls, the comparison of correlation patterns across different data samples reveals a striking degree of robustness. Our findings in Figure 1 align closely with those of Figure 2, which is constructed on an earlier sample of the NBA data studied by Berri et al. (2006) and with those from Euroleague in Figure 3.

This robustness suggests the presence of a stable underlying structure, a data generation process, within basketball statistics, which opens the door to more reliable model-based approaches to performance evaluation. Measurement without theory does not help, but it offers some statistical background for the implementation of theory-based measurement.

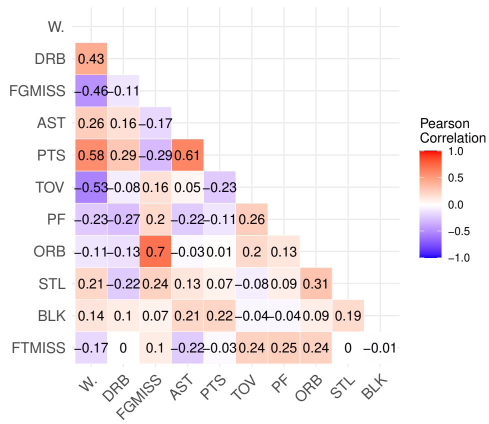

Figure 1: Correlation between Win Percentage and Box-Score Stats for NBA teams, seasons 2021-22 to 2024-25

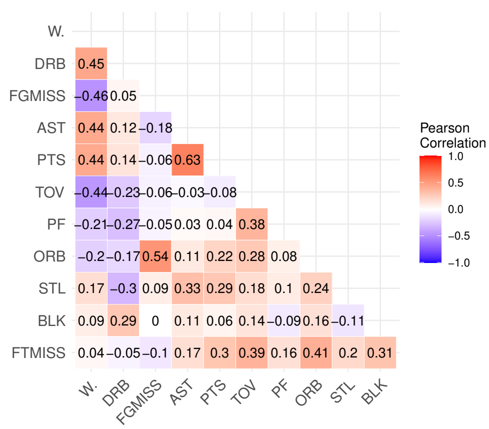

Figure 2: Correlation between Win Percentage and Box-Score Stats for NBA teams, seasons 1992-93 to 2004-05, omitting Season 1998-99

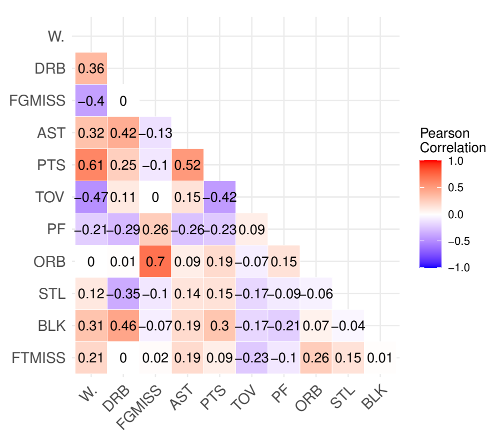

Figure 3: Correlation between Win Percentage and Box-Score Stats for Euroleague teams, seasons 2022-23 to 2024-25,

3 Reinterpreting WINSCORE as a Model-Based Framework

Theory-based measurement relies on a formal model to account for the interactions among the relevant variables in a comprehensive way. The model-based approach unfolds through a sequence of well-defined steps.

The first step is model specification, where variables are classified into exogenous or endogenous and their interdepence is captured in equations. In this stage, the data for endogenous variables are conceptually decomposed into two components: structure and noise (James et al., 2013). The structural component captures systematic relationships that are invariant to the specific sample and can thus be used for prediction and policy analysis, particularly to evaluate how changes in exogenous variables affect endogenous outcomes. In contrast, the noise component is sample-specific and does not inform point predictions or simulations directly. However, it plays a crucial role in quantifying uncertainty around predictions, for instance, through the construction of confidence intervals. The model may also incorporate relationships among exogenous variables.

Model equations are typically formalized through functional equations involving a set of unknown parameters. The second step involves assigning numerical values to these parameters. This can be achieved through estimation, using the available data on the model's variables, or through calibration, which leverages information external to the dataset (Cooley, 1997).

Once the parameters have been estimated or calibrated, it becomes possible to recover the empirical counterpart of noise in the form of fitted residuals. These residuals serve a critical role in model validation. Validation involves examining whether the statistical properties of the residuals align with the assumptions underpinning the estimation process. Deviations may indicate model misspecification (Favero, 2001). Further validation can be pursued by comparing the specification of the model to alternative specifications or by testing the stability of key parameters across different subsamples.

The final step involves putting the model to work via simulation. By simulating the model under a baseline scenario—where all exogenous variables are held at their average values—and comparing it to a counterfactual scenario in which one or more exogenous variables are altered, it is possible to assess the impact of such changes on the endogenous variables. This step is made possible by the fact that the model makes explicit the causal links between variables (Terner and Franks, 2021).

The remainder of this section demonstrates how the Winscore approach can be reinterpreted within a model-based framework, and how each of the modelling steps outlined above can be operationalized in the context of Winscore.

3.1 Winscore Specification and Estimation

The Winscore approach uses the number of WINS in a regular season as the measurable counterpart of performance. The main theoretical hypothesis is that the key concept to determine performance is how efficiently teams use **possession**.

A possession starts when one team gains control of the ball and ends when that team gives it up (in other words, an offensive rebound would start a new play, not a new possession). Possession totals are guaranteed to be approximately the same for the two teams in a game, approximately because ends of quarter possessions might not be evenly distributed across a team and its opponent. However, over a season, the effect of end of quarter possessions averages out at zero and possessions of a team and its opponent are the same, apart from possible small sample noise.

Given a database with t seasons and i teams, possessions can be categorized into Earned Possessions and Allowed Possessions:

$$\begin{aligned} EP_{i,t} &= FGA_{i,t} + 0.45 * FTA_{i,t} + TOV_{i,t} - ORB_{i,t} \\ AP_{i,t} &= OTOV_{i,t} + DRB_{i,t} + TEAMR_{i,t} + OFG_{i,t} + 0.45 * OFT_{i,t} \\ EP_{i,t} &\approx AP_{i,t} \end{aligned}$$

As noted by (Berri et al., 2006) $TEAMR_{i,t}$ are not available from the Box-Score statistics, but they can be reconstructed by exploiting the fact that $EP_{i,t} \approx AP_{i,t}$. A measure of performance is constructed by taking the difference of points made per earned possession and points made by the opponents per allowed possession as:

$$PTSxEP_{it} - PTSAxAP_{i,t}$$

The Winscore model is then specified as follows:

$$
\begin{aligned}
W_{it} &= \beta_0 + \beta_1 \left(PTSxEP_{it} - PTSAxAP_{i,t}\right) + u_{it} \qquad (1)\\
u_{it} &\sim N.I.D\left(0, \sigma^2\right)\\
PTSxEP_{it} &= \frac{PTS_{i,t}}{EP_{i,t}}\\
PTSAxAP_{i,t} &= \frac{PTSA_{i,t}}{AP_{i,t}}\\
EP_{i,t} &= FGA_{i,t} + 0.45 * FTA_{i,t} + TOV_{i,t} - ORB_{i,t}\\
AP_{i,t} &= OTOV_{i,t} + DRB_{i,t} + TEAMR_{i,t} + OFG_{i,t} + 0.45 * OFT_{i,t}\\
PTS_{i,t} &= 1 * FT_{i,t} + 2 * 2PFG_{i,t} + 3 * 3PFG_{i,t}\\
PTSA_{i,t} &= 1 * OFT_{i,t} + 2 * O2PFG_{i,t} + 3 * O3PFG_{i,t}
\end{aligned}
$$

The model is made up of seven equations, but only the first one is stochastic and depends on unknown parameters. The interpretation of the unknown parameters in this equation is very intuitive: β_0 captures the performance over a season of the average team (it will be estimated at one-half of the number of games played n), while β_1 measures the impact of the efficiency measure in determining the deviation of each team's performance from that of the average team. Model estimation can be implemented by single-equation methods applied on the first equations. Table 1 reports the results of estimating the WINSCORE model on a pooled cross-section of box-score data for all teams for a benchmark NBA sample used by Berri et al. (2006), and for the post-COVID seasons in the NBA, and the Euroleague.[3]. As the number of games played in the regular season is 82 in the NBA and 34 in the Euroleague to facilitate comparability Table (1a) reports the results with total Wins as dependent variable while Table (1b) reports the results with the percentage of Wins as dependent variable.

[3]The presence of fixed effect for teams and time-effect for season was checked and the relevant coefficients were found to be not statistically different from zero

Table 1: **Wins and Efficiency in the NBA and the Euroleague**

(a) Regression of wins on efficiency: NBA 1994-2005 (Berri et al., 2006), NBA 2021–2024, and Euroleague 2022–25

	Dependent variable: Wins in Regular Season		
	NBA 1994-2005	**NBA 2021–2024**	**Euroleague 2022–25**
Intercept	41.00***	41.00***	17.00***
	(0.17)	(0.33)	(0.26)
$(PTSxEP_{i,t} - PTSAxAP_{i,t})$	257.16***	237.38***	78.46***
	(3.40)	(7.11)	(4.34)
Observations	316	90	54
Multiple $\mathbf{R}^2$	0.95	0.93	0.86
Adjusted $\mathbf{R}^2$	0.95	0.93	0.86
F Statistic	5718***	1115***	326.2***

$^{***}p < 0.001$

(b) Regression of Percentage of Wins on efficiency: NBA 1994-2005 (Berri et al., 2006), NBA 2021–2024, and Euroleague 2022–25

	Dependent variable: Percentage of Wins in Regular Season		
	NBA 1994-2005	**NBA 2021–2024**	**Euroleague 2022–25**
Intercept	0.50***	0.50***	0.50***
	(0.002)	(0.007)	(0.04)
$(PTSxEP_{i,t} - PTSAxAP_{i,t})$	3.13***	2.89***	2.30***
	(0.041)	(0.086)	(0.127)
Observations	316	90	54
Multiple $\mathbf{R}^2$	0.95	0.93	0.86
Adjusted $\mathbf{R}^2$	0.95	0.93	0.86
F Statistic	5718***	1115***	326.2***

$^{***}p < 0.001$

The estimated parameters are highly significant an stable over the two different samples for the NBA. The intercept in all regressions, as expected, captures the performance of the average team [4] The slope coefficient captures the importance of the adopted efficiency measures in explaining deviations of each teams' performance from that of the average team efficiency. This coefficient is positive, highly significant and of a size which is robustly estimated across different samples in the NBA. However, there is a significant difference in the impact of efficiency on Wins between the NBA and the Euroleague, which features a smaller

[4]The results in Table 1 are obtained by running all models using a demeaned measure of efficiency, as the sample mean of this variable is very close to zero but not exactly equal to zero.

coefficient in the projections of percentage of Wins on efficiency. This smaller coefficient is explained by the fact that the variance of the efficiency measure in the Euroleague is higher than that of the equivalent variable for the NBA. This evidence could be interpreted as a signal of higher "competitive balance" (Zimbalist, 2002) in the NBA. [5]

3.2 Winscore Validation

After estimation, validation becomes possible. A natural way to proceed here is via the assessment of the capability of Winscore to outperform alternative models in predicting W_{it}, and here the obvious candidate is a prediction of W_{it} based on the PIR approach. To this end, after the estimation of the Winscore equation 1, an alternative equation, based on PIR, can be specified as:

$$\begin{aligned} W_{it} &= \gamma_0 + \gamma_1 \left(PIR_{it} - OPIR_{i,t} \right) + v_{it} \\ v_{it} &\sim \text{i.i.d. } \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2}$$

where PIR_{it} is the PIR of team i in season t, and $OPIR_{it}$ is the PIR of the opponents.

After estimation of equations (1) and (2), the following "encompassing model" (Mizon and Richard, 1986) is estimated:

$$\begin{aligned} W_{it} &= \delta_1 \hat{W}_{it}^{WS} + \delta_2 \hat{W}_{it}^{PIR} + \epsilon_{it} \\ \epsilon_{it} &\sim \text{i.i.d. } \mathcal{N}(0, \sigma^2) \end{aligned} \tag{3}$$

where $\hat{W}_{it}^{WS}$ and $\hat{W}_{it}^{PIR}$ are the predicted wins from the two alternative models. The estimated parameters in equation (3) indicate the weights of the prediction from the two models in their optimal combination to forecast the common dependent variable. The more WINSCORE dominates, the closer we are to a situation in which $\delta_1 = 1,\ \delta_2 = 0$.

Table (2) reports the results from the estimation of equation (2) on different leagues and samples.

[5] Interestingly, the average points scored for possession are higher in the Euroleague than in NBA, debunking the myth that European basketball features better defenses than the NBA.

Table 2: Regression of wins on PIR factor: NBA (Berri), NBA 2021–2024, and Euroleague 2022–25

	Dependent variable: wins		
	NBA (Berri et al., 2006)	**NBA 2021–2024**	**Euroleague 2022–25**
Intercept	41.00***	41.00***	17.00***
	(0.169)	(0.367)	(0.335)
PIR factor	0.016***	0.014***	0.011***
	(0.000285)	(0.000475)	(0.000842)
Observations	316	90	54
Multiple R^2	0.91	0.91	0.76
Adjusted R^2	0.91	0.91	0.76
F Statistic	3219***	902.7***	168***

$^{***}p < 0.001$

In both the NBA and Euroleague specifications, the estimated coefficient on the PIR factor is positive and highly significant, indicating a robust relationship between player impact rating and team wins. The NBA regression explains 91 percent of the variance in wins compared to 76 percent in the Euroleague.

However, the results of the encompassing test reported in Table 3 show that the WINSCORE model uniformly dominates PIR. For all data-sets considered encompassing regressions, the coefficient on the WINSCORE prediction is positive statistically different zero and not statistically different from one, whereas the coefficient associated with the PIR prediction is always not statistically different from zero. Moreover, the joint hypothesis $\delta_1 = 1,\ \delta_2 = 0$ is never rejected.

Table 3: Encompassing regressions combining WINSCORE and PIR predictions: NBA (Berri), NBA Model, and Euroleague Model (rounded to two decimals)

	Dependent variable: wins		
	NBA (Berri et al., 2006)	**NBA 2021–2024**	**Euroleague 2022–25**
Pred. WINSCORE	0.92***	0.77***	1.08***
	(0.06)	(0.17)	(0.18)
Pred. PIR	0.08	0.23	-0.08
	(0.06)	(0.17)	(0.18)
Observations	316	90	54
Multiple R^2	0.9952	0.9947	0.9892
Adjusted R^2	0.9952	0.9946	0.9888
F Statistic	32500***	8314***	2391***

$^{***}p < 0.001$

3.3 Winscore Simulation

After estimation (or calibration) of all unknown parameters, the model can then be used to attribute weigths to statistics by simulating their impact on predicted wins in the following steps:

- Generate via the model a predicted value for wins in the case all statistics are kept at their average. This is called the baseline scenario simulation.
- Generate via the model a predicted value for wins in case all the statistics are kept at their average except the one, whose effect is to be evaluated.
- The difference between wins in the alternative scenario and wins in the baseline scenario gives the impact of the statistic on WINs.
- Point estimate of the impact are obtained via deterministic simulation, while the the statistical distribution of the impact can be obtained via stochastic simulation by taking uncertainty around the estimated coefficients into account.

Note that the model-based procedure takes all feedbacks into account: one more 3-points shots made gives the team three points more at the cost of employing a possession.

Table 4 reports the weights derived by model simulation after model estimation based on the Euroleague data in the Post-Covid periods and compares them with the weights reported by Berri et al. (2006) derived by the same technique after estimation based on the NBA data form seasons 1994 to 2005 excluding season 1999 due to the players' strike. The difference in the estimated parameters in the Winscore model reported in Table 1 generated some difference in the weights of the different statistics for the two leagues.[6] These differences are not large and they can be reconciled by the logic of the model; for example, in the league with the higher competitive balance (the NBA) the contribution a three-point shot made to wins is expected to be higher than that in a league with a lower competitive balance (the Euroleague).

[6]Personal Fouls, Blocked shots and Assists do not directly enter the model but, following Berri et al. (2006). They are weighted by using auxiliary regressions that link them to variables included in the model. Specifically opponent's free throws made are regressed on personal fouls to learn that each personal foul is worth about one free throw made by the opponent, and opponent's two-point field goals made are regressed on blocked shots, to learn that each blocked shot reduces the opponent's two-point field goals made by 0.65. With a similar method the value of an assist is established at 0.67 the value of a possession statistic in the model without assist.

Table 4: The Value of Statistics in Terms of Wins

Statistics	Impact on Wins (Euroleague)	Impact on Wins (NBA (Berri et al., 2006))
Scoring Statistics		
Three-point field goals made	+0.059	+0.066
Opponent's three-point field goals made	-0.059	-0.066
Two-point field goals made	+0.027	+0.033
Opponent's two-point field goals made	-0.027	-0.033
Free throws made	+0.016	+0.018
Opponent's free throws made	-0.016	-0.018
Missed field goals	-0.036	-0.034
Missed free throws	-0.016	-0.015
Possession Statistics		
Offensive rebounds	+0.036	+0.034
Turnovers	-0.036	-0.034
Defensive rebounds	+0.036	+0.034
Team rebounds	+0.036	+0.034
Opponent's turnovers	+0.036	+0.034
Steals	+0.036	+0.034
Personal Fouls and Blocked Shots		
Personal fouls	-0.016	-0.018
Blocked shots	+0.017	+0.021
Assist	+0.018	+0.022

4 Interpreting the Winscore Model

After the attribution of weights by simulation to each statistic, the outcome of the model simulation has the following intuitive linear interpretation:

$$
\begin{aligned}
W_{it}^{WS} &= \frac{n}{2} + WINSEFF_{it} - OWINSEFF_{it} \qquad (4) \\
WINSEFF_{it} &= SCSTAT_{it} + POSSTAT_{it} + PFBLK_{it} \\
SCSTAT_{it} &= 3PFG_{i,t} * w^{3P} + 2PFG_{i,t} * w^{2P} + FT_{i,t} * w^{FT} + \\
&+ (FGA_{i,t} - 3PFG_{i,t} - 2PFG_{i,t}) * w^{FGM} + (FTA_{i,t} - FT_{i,t}) * w^{FTM} \\
POSSTAT_{it} &= w^{POS}(ORB_{i,t} + DRB_{i,t} + STL_{i,t} - TOV_{i,t}) \\
PFBLK_{it} &= w^{BLK} * BLK_{i,t} + w^{PF} * (PF_{i,t} - FD_{i,t}) \\
OWINSEFF_{it} &= OSCSTAT_{it} + OPOSSTAT_{it} + OPFBLK_{it} \\
OSCSTAT_{it} &= O3PFG_{i,t} * w^{3P} + O2PFG_{i,t} * w^{2P} + OFT_{i,t} * w^{FT} + \\
&+ (OFGA_{i,t} - O3PFG_{i,t} - O2PFG_{i,t}) * w^{FGM} - (OFTA_{i,t} - OFT_{i,t}) * w^{FTM} \\
OPOSSTAT_{it} &= w^{POS} * (OORB_{i,t} + ODRB_{i,t} + OSTL_{i,t} - OTOV_{i,t}) \\
OPFBLK_{it} &= w^{BLK} * OBLK_{i,t} + w^{PF} * (OPF_{i,t} - OFD_{i,t})
\end{aligned}
$$

where $\left[w^{3P}, w^{2P}, w^{FT}, w^{FGM}, w^{FTM}, w^{BLK}, w^{PF}\right]$ are the weights reported in Table 4.

Deviations of each team's performance from that of the average team depend on the difference between each team and their opponents weighted measure of performance based on Winscore' weights. Therefore, the performance of each team can be constructed by applying to the measure of performance for each team $WINSEFF_{it}$ two corrections: one for the performance of the opponents $OWINSEFF_{it}$ and one for the performance of the average team $\frac{n}{2}$.

This interpretation of the model, based on linearization, allows to apply the measure of performance constructed using data for Teams to Individual Players. Before taking this step in the next section it is probably worth taking a look at Figure 4 which reports a cross plot of the Wins predicted for NBA teams over the seasons 1992-93 to 2004-5 (omitting season 1998-99) by the exact Winscore model (1) and by its linearized version (4). There is a clear evidence of a very strong associations between the two variables, with some exceptions only on the tails, to be expected as a consequence of linearization. The data for Boston Celtics, highlighted in green in the graph, confirm the very strong association between the predictions of the exact and linearized models singling out a specific team over the time-series of seasons.

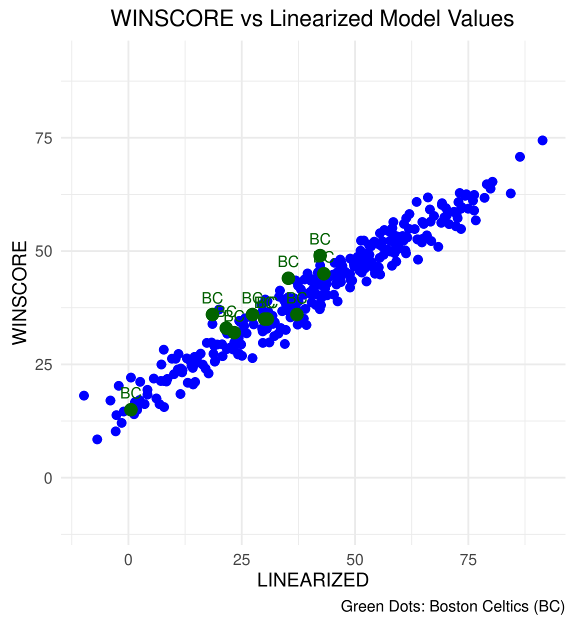

Figure 4: Wins predicted by the Winscore model vs Wins predicted by the linearized Winscore model

5 From Team to Players: Season Data

Given the availability of statistics for each player j during a given season, a measure of player performance can be constructed by exploiting Equation (4). Following Berri et al. (2006), the approach consists of the following steps:

- Compute $WINSEFF_j$ by aggregating scoring statistics, possession statistics, personal fouls (PF), and blocks (BLK).
- Compute an individual-level proxy for $OWINSEFF_j$ by averaging the $WINSEFF$ of all players k in the league who play the same role as player j. To account for differences in court time across players, first put fictitiously player k on court all time by multiplying his measure of efficiency by $\frac{TOTMIN_k}{MIN_k}$, where $TOTMIN$ denotes the total minutes available to player j in the season ($40 \cdot n$ in the Euroleague or $48 \cdot n$ in the NBA, assuming no overtime), then adjust this projection to match player j's actual court time by multiplying the result by $\frac{MIN_j}{TOTMIN_j}$.
- Compute the contribution of the average player to the wins of the average team over the same court time as player j using: $\frac{MIN_j}{TOTMIN_j} \cdot \frac{0.5 \cdot n}{5}$.

Using this procedure, the following measure is defined:

$$WINSCORE_j^B = WINSEFF_j - OWINSEFF_j^{adj,B} + \frac{MIN_j}{TOTMIN_j} \cdot \frac{0.5 \cdot n}{5}, \tag{5}$$

$$OWINSEFF_j^{adj,B} = \left(\frac{1}{N_{\mathrm{role}(j)}} \sum_{k \in \mathrm{role}(j)} WINSEFF_k \cdot \frac{TOTMIN_k}{MIN_k} \right) \cdot \frac{MIN_j}{TOTMIN_j}. \tag{6}$$

This player-level efficiency measure, *Winscore*, can be interpreted as the player's contribution to team performance in terms of wins over a season. If this interpretation holds, then the sum of individual player contributions should approximate the predicted number of team wins according to the WINSCORE model:

$$\sum_{j=1}^{n} WINSCORE_j^B \approx \text{Team Wins}, \tag{7}$$

where $WINSCORE_j^B$ is the efficiency score for player j, and n is the number of players on the team.

Importantly, the measure incorporates not only each player's individual performance, but also the performance of their average opponents and a league-wide reference average.

This metric corrects for variation in playing time by first projecting each player's statistics as if they had been on the court for the entire season, and then rescaling the result based on actual minutes played.

However, court time is not exogenous; it is the result of coaching decisions based on subjective assessments of player ability. Projecting players' performance to full-season minutes can bias efficiency scores, especially for those who played very little. For instance, an NBA player who plays only one minute and scores a three-pointer would unrealistically be projected to score 144 points over a full game[7].

One solution to this issue is to set a minimum playing-time threshold and drop players below it. However, this introduces arbitrariness regarding the cutoff.

We propose an alternative solution that explicitly addresses the endogeneity of playing time. Instead of projecting all players to full minutes, we adjust the opponent-level efficiency using only those players who played a similar amount of time. Specifically, we average $WINSEFF$ across players in the same role whose court time lies within 10% of that of player j.

Our modified Winscore measure for player j, $WINSCORE_j^M$, is then defined as:

[7] The highest number of points ever scored by a player in an NBA regular season game is 100, achieved by Wilt Chamberlain on March 2, 1962. Playing for the Philadelphia Warriors against the New York Knicks, Chamberlain remained on court for the entire game, which ended in a 169–147 victory.

$$WINSCORE_j^M = WINSEFF_j - OWINSEFF_j^{adj} + \frac{MIN_j}{TOTMIN_j} \cdot \frac{0.5 \cdot n}{5}, \tag{8}$$

$$OWINSEFF_j^{adj} = \frac{1}{N_j^\Delta} \sum_{\substack{k \in \text{role}(j) \\ MIN_k \in [0.9 \cdot MIN_j,\ 1.1 \cdot MIN_j]}} WINSEFF_k, \tag{9}$$

where N_j^Δ is the number of players in the same role as j whose court time falls within 10% of MIN_j.

To illustrate the validity of the proposed measures, Table 5 reports aggregate data on wins in the Euroleague for the 2024–25 season. For each of the eighteen teams, the table displays the actual number of regular-season victories alongside four sets of model-based predictions: the efficiency-based exact measure using team-level data (**WS**); the linearized WINSCORE derived from team-level data (**Lin. WS**); and two player-level aggregations of individual contributions (**PWS**), computed as $\sum_{i=1}^{n} WINSCORE_{i,j}^B$ and $\sum_{i=1}^{n} WINSCORE_{i,j}^M$, respectively.

Table 5: Model Predictions vs. Actual Wins by Team

Team	**Wins**	**WS**	**Lin. WS**	$\sum_{i=1}^{n} WINSCORE_{i,j}^B$	$\sum_{i=1}^{n} WINSCORE_{i,j}^M$
ASV	13	12.5	13.5	18.2	13.0
BAR	20	21.2	20.1	27.2	22.8
BAS	14	15.0	20.1	19.7	20.5
BER	5	3.6	0.5	15.5	-1.6
IST	20	22.5	27.0	32.7	24.7
MAD	20	19.6	27.6	20.1	18.7
MCO	21	21.1	15.3	25.5	18.4
MIL	17	16.2	18.3	30.5	19.8
MUN	19	15.8	16.0	25.6	18.6
OLY	24	22.0	22.4	30.3	24.6
PAN	22	22.7	25.4	34.3	23.3
PAR	16	18.5	12.5	22.0	20.2
PRS	19	17.5	9.6	24.4	19.7
RED	18	18.2	15.3	22.0	13.3
TEL	11	13.8	15.4	28.0	15.7
ULK	23	19.4	23.6	23.6	13.4
VIR	9	11.3	8.6	20.9	13.2
ZAL	15	14.7	14.8	17.0	9.1

The table highlights two key results. First, both the exact and linearized WINSCORE models provide reasonable approximations to actual team victories, validating the underlying approach. Second, the player-level aggregation using the modified adjustment ($WINSCORE^M$) yields a better match to team-level wins compared to the unadjusted version ($WINSCORE^B$).

This supports the hypothesis that correcting for the endogeneity of court time improves the reliability of individual-level efficiency estimates.

By contrast, $\sum_{i=1}^{n} WINSCORE_{i,j}^{B}$ tends to overestimate team performance due to the upward bias introduced when players with limited minutes are virtually extrapolated to full-game equivalents. This underscores the importance of appropriately accounting for selection effects in efficiency modeling.

6 From Team to Players: Single Game data

Our proposed $WINSCORE_j^M$ is very naturally extended when single game data are available, and the correction for the opponents performance and for the different amount of time spent on court by the different players can be dealt with in a more precise manner. In this case players they can be matched more precisely with their opponents without referencing to an average player to make the correction for the opponent's Winscore.

Consider the case in which statistics from a given game are available for all players of two teams, 1 and 2. The following procedure can be used to compute an individual measure of efficiency

- Group players by role, say back-court and front-court, and compute $WINSEFF_{j,1}^{r}$ and $WINSEFF_{j,2}^{r}$, $r = BC, FC$
- rank players by the time spent on court $MIN_{j,1}^{r}$ and $MIN_{j,2}^{r}$
- compute the player adjustment by considering the player in the same role who has the same rank with him in terms of minute spent on court and put the two players on court for the same amount of time.
- compute the contribution of the average player to that of the average team when the average player has been on court the same amount of time with player j

The following measure of efficiency is then computed:

$$WINSCORE_{j,1}^{r} = WINSEFF_{j,1}^{r} - WINSEFF_{j,2}^{r}\left(\frac{MIN_{j,1}^{r}}{MIN_{j,2}^{r}}\right) + \frac{MIN_{j,1}^{r}}{TOTMIN_{j,1}^{r}} * \frac{0.5}{5} \quad (10)$$

The sum of the Winscore efficiency of each player at the team level gives the expected Wins in the game considered. As expected Wins will not be the same for the two teams, the WINSCORE measure of efficiency takes into account not only performance relative to the opponents and the average players but also the outcome of the game.

To illustrate the measure, Table 6 reports data for the Euroleague game Virtus Bologna-Barcellona, played in April 2025 and won by Barcelona 91-87. Several comments are in order here. First, extracting individual measures of performance from data on a single game differs significantly from doing so over an entire season. In season-long data, errors tend to average out across many games, which is not the case for a single-game analysis. For example, consider the problem of assigning roles to players. With season data, one can rely on the official role classifications—Guard, Forward, and Center in the EuroLeague, or the more detailed classification used in the NBA (Center, Power Forward, Small Forward, Point Guard, and Shooting Guard). While such classifications may include some misassignments, these tend to average out over a season. In contrast, in a single game, due to injuries or tactical adjustments, coaches may assign players to roles different from their official designation. However, because we have detailed data from the game itself, we can reclassify players more appropriately into two functional groups: Front-Court (FC) and Back-Court (BC), and match them accordingly.

Second, the problem of matching each player with an opponent can be addressed by assigning a specific opponent, rather than comparing against an average player in the same role. Likewise, discrepancies in playing time can be handled by applying minor adjustments among players within the same group who played similar minutes during the game.

In Table 6, after classifying players from both teams as either BC or FC, they are sorted by minutes played within their group and then matched with their counterparts. If the two teams have different roster sizes, some players may be matched more than once. In the example at hand, since Barcelona had one fewer player than Virtus, both Pajola and Hackett are matched with Abrines.

Once players are classified and matched to opponents with adjusted court time, their WINSCORE can be computed using Equation (10). The final two columns of the table report both WINSCORE and PIR for each player. The total team WINSCORE can be interpreted as the contribution of that game to the team's total wins for the season. For the game considered, Barcelona's contribution is 0.583 and Virtus's is 0.303. These contributions approximately sum to one, and each team's total is the sum of individual player contributions. When both teams contribute similarly, it indicates a close game. In unbalanced games, one team's contribution would approach one, while the other's would approach zero. Therefore, WINSCORE also reflects the game outcome. In this case, the close values reflect a tightly contested game, with Barcelona winning by four points—a result also driven by the noise component in the data in addition to the structural elements captured by the model.

Notably, PIR and WINSCORE are not correlated. For instance, Parra has the lowest WINSCORE on Barcelona but the third-highest PIR. This is because Diouf outperformed

Parra in their head-to-head comparison, and WINSCORE is computed relative to a relevant opponent and the average player. PIR, by contrast, is an absolute measure that does not account for opponent context, and thus often gives a very different picture.

The WINSCORE analysis reveals that Barcelona's Back-Court outperformed Virtus's, whereas Virtus's Front-Court outperformed Barcelona's. This contrast is not captured by the PIR measure.

Finally, while scoring has a dominant weight in PIR, the WINSCORE metric offers a more comprehensive assessment of player performance.

Table 6: Euroleague: April 2025 BARCELLONA - VIRTUS 91-87

(a) Barcellona: Players (surnames only), WINSCORE and PIR

Player	Seconds	Role	Opponent	Opp. Seconds	WINSCORE	PIR	Points
SATORANSKY	1756	BC	CORDINIER	1522	0.303	19	11
PUNTER	1744	BC	CLYBURN	1409	0.189	22	20
ANDERSON	1489	BC	HOLIDAY	1254	-0.123	12	12
BRIZUELA	1278	BC	MORGAN	1228	0.268	10	10
ABRINES	358	BC	HACKETT	925	0.063	0	0
ABRINES	358	BC	PAJOLA	916	0.033	0	0
PARKER	1366	FC	SHENGELIA	1706	0.045	7	10
PARRA	1251	FC	DIOUF	909	-0.143	13	10
HERNANGOMEZ	1114	FC	ZIZIC	894	0.072	12	9
VESELY	917	FC	POLONARA	755	-0.053	13	9
FALL	369	FC	AKELE	482	-0.072	-2	0
Sum	12000			12000	0.583	106	91

(b) Virtus Bologna: Players (surnames only), WINSCORE and PIR

Player	Seconds	Role	Opponent	Opp. Seconds	WINSCORE	PIR	Points
CORDINIER	1522	BC	SATORANSKY	1756	-0.135	10	11
CLYBURN	1409	BC	PUNTER	1744	-0.035	13	15
HOLIDAY	1254	BC	ANDERSON	1489	0.208	16	16
MORGAN	1228	BC	BRIZUELA	1278	-0.155	-2	5
HACKETT	925	BC	ABRINES	358	-0.086	0	0
PAJOLA	916	BC	ABRINES	358	-0.009	3	0
SHENGELIA	1706	FC	PARKER	1366	0.086	12	17
DIOUF	909	FC	PARRA	1251	0.180	13	6
ZIZIC	894	FC	HERNANGOMEZ	1114	0.016	13	12
POLONARA	755	FC	VESELY	917	0.106	9	5
AKELE	482	FC	FALL	369	0.134	2	0
Sum	12000			12000	0.308	89	87

7 Conclusion

This paper has revisited the WINSCORE methodology and reformulated it within a rigorous, model-based framework for evaluating player performance in professional basketball. Moving beyond purely descriptive or ad hoc aggregation methods, the WINSCORE approach is grounded in theory, explicitly linking team wins to efficiency in managing possessions. This provides a coherent foundation for assigning value to individual player statistics.

Empirical estimation using data from both the NBA and Euroleague shows that the model effectively captures variation in team success. In particular, encompassing tests demonstrate that WINSCORE subsumes the predictive power of the widely used Performance Index Rating (PIR), in the context of different samples and different leagues. Simulations based on the estimated model yield interpretable weights for each statistic, which are stable across samples and consistent with theoretical expectations.

We further extend the framework to derive player-level efficiency metrics at both the season and single-game levels, incorporating opponent adjustments and time normalization. The model-based intepretation of WINSCORE allows to produce a new measure of players efficiency that can be applied on data from seasons and single games. These extensions retain the structural rigour of the model while offering practical tools for applied performance analysis.

Our case study, based on data from a specific game, illustrates the advantages of modified WINSCORE over PIR. Our modified WINSCORE accounts for the context-specific nature of each game, evaluates players relative to relevant opponents by taking into account that time spent of court is the outcome of a choice by coaches based on their assessment of the quality of each player , and incorporates the team's performance into the assessment of individual contributions.

Overall, our findings support the use of model-based methods for player evaluation and highlight WINSCORE as a robust alternative to traditional metrics that lack a clear theoretical foundation.

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8 Appendix: the Data

Data for the Euroleague have been retrieved using the R package **euroleaguer** and the unofficial API wrapper for 'Euroleague' and 'Eurocup' basketball API. Data for the NBA have been webscraped from Basketball Reference using an R code provided in our replication package, which is available from the authors upon request.
The following variables are used in our analysis:

Variable	Description
SeasonCode	Identifier for the competition season
GameCode	Unique identifier for each game
TeamCode	Identifier for the team
Seconds	Total seconds played by the player
PTS	Total points scored
2PM	Two-point field goals made
2PA	Two-point field goals attempted
3PM	Three-point field goals made
3PA	Three-point field goals attempted
FTM	Free throws made
FTA	Free throws attempted
OREB	Offensive rebounds
DREB	Defensive rebounds
REB	Total rebounds
AST	Assists
STL	Steals
TO	Turnovers
BLK	Blocks made
BLKA	Shots blocked against the player
FC	Personal fouls committed
FD	Personal fouls drawn
PIR	Performance Index Rating
FG%	Overall field-goal percentage
2P%	Two-point field-goal percentage
3P%	Three-point field-goal percentage
FT%	Free-throw percentage
Year	Calendar year of the game

Table 7: Description of box-score statistics