

Playing Time, Points, and Possession: Evaluating Individual Player Efficiency in the Turkish Basketball League through a Parallel Network SBM Data Envelopment Analysis

Oynama Süresi, Sayı ve Top Hakimiyeti: Paralel Ağ Yapılı SBM
Veri Zarflama Analizi ile Türkiye Basketbol Ligi'nde Bireysel
Oyuncu Etkinliğinin Değerlendirilmesi

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ABSTRACT

This study develops a parallel non-homogeneous Network Slacks-Based Measure Data Envelopment Analysis (NDEA-SBM) model to evaluate the individual efficiency of professional basketball players in the Turkish Basketball League (TBL) over a three-year period covering the 2023–24, 2024–25, and 2025–26 seasons. Each player is modeled as a two-stage parallel system in which playing time is simultaneously allocated to offensive and defensive production. The offensive stage transforms minutes played, field-goal attempts, and free-throw attempts into points, field goals made, free throws made, and offensive rebounds, whereas the defensive stage transforms minutes played into defensive rebounds, assists, steals, and blocks; turnovers are incorporated into the model as an undesirable output. For observations with zero blocks, the corresponding slack term is excluded from the SBM denominator; this adjustment applies to 68 of the 300 observations. Across the 300 player-season observations, the pooled mean overall efficiency is calculated as 0.7074, with a moderate structural asymmetry observed on average between offensive efficiency (0.7401) and defensive efficiency (0.6748), while the two stages are nearly balanced in the 2024–25 season. Slack analysis identifies unused playing time and deficiencies in offensive rebounds as the primary sources of inefficiency in the offensive stage, and unused court time and deficiencies in defensive rebounds as the primary sources of inefficiency in the defensive stage. Super-efficiency analysis ranks 40 fully efficient observations; panel analysis of the 16 players appearing on the list across the three seasons reveals individual efficiency trajectories that cannot be captured by single-season statistics.

Keywords: Data Envelopment Analysis, Network DEA, Slack-Based Measure, Basketball Efficiency, Turkish Basketball League, Undesirable Outputs

Öz

Bu çalışma, Türkiye Basketbol Ligi'nde (TBL) profesyonel basketbol oyuncularının bireysel etkinliğini 2023–24, 2024–25 ve 2025–26 sezonlarını kapsayan üç yıllık bir dönemde değerlendirmek amacıyla paralel homojen olmayan Ağ Yapılı Artık Temelli Ölçüm Veri Zarflama Analizi (NDEA-SBM) modeli geliştirmektedir. Her oyuncu, oynama süresinin aynı anda hücum ve savunma üretimine tahsis edildiği iki aşamalı paralel bir sistem olarak modellenmektedir. Hücum aşaması; dakika, şut denemesi ve serbest atış denemesini sayı, isabetli şut, isabetli serbest atış ve hücum ribauntuna dönüştürürken savunma aşaması dakikayı savunma ribaundu, asist, top çalma ve blok'a dönüştürmekte; top kayıpları ise istenmeyen çıktı olarak modele dahil edilmektedir. Blok sayısının sıfır olduğu gözlemler için ilgili slack terimi SBM paydasından çıkarılmış; bu düzeltme 300 gözlemin 68'ini kapsamaktadır. 300 oyuncu-sezon gözlemi genelinde havuzlanmış ortalama genel etkinlik 0,7074 olarak hesaplanmış, hücum etkinliği (0,7401) ile savunma etkinliği (0,6748) arasındaki ılımlı yapısal asimetri ortalama gözlenmiş, 2024/25 sezonunda iki aşama neredeyse dengelenmiştir. Slack analizi, hücum aşamasında kullanılmayan oynama süresi ile hücum ribaundu eksikliği, savunma aşamasında ise kullanılmayan saha süresini ve savunma ribaundunu temel verimsizlik kaynakları olarak belirlemiştir. Süper etkinlik analizi 40 tam etkin gözlemi sıralamış; üç sezon boyunca listeye giren 16 oyuncunun panel analizi, tek sezonluk istatistiklerle yakalanamayan bireysel etkinlik yörüngelerini ortaya koymuştur.

Anahtar Kelimeler: Veri Zarflama Analizi, Ağ VZA, Artık Temelli Ölçüm, basketbol oyuncusu etkinliği, Türkiye Basketbol Ligi, istenmeyen çıktılar

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Introduction

Measuring how efficiently a basketball player uses his court time remains an unsolved problem. The most widely used individual performance indices — Player Efficiency Rating, Win Shares, Box Plus/Minus — aggregate box-score statistics through weighting schemes whose parameters are set by the analyst rather than derived from the data. More fundamentally, these metrics make no reference to a production frontier: they report raw output, not how much of a player's potential output he actually realises given his resource use.

Data Envelopment Analysis (DEA), introduced by Charnes et al. (1978) and extended to variable returns to scale by Banker et al. (1984), evaluates each decision-making unit relative to an empirically constructed best-practice frontier. Each unit receives the input and output weights that place it in the most favourable light, and the resulting efficiency score measures its distance from that frontier. The framework has been applied widely in professional sports — in football (Haas, 2003a, 2003b), baseball (Anderson and Sharp, 1997), and basketball at both the team (Moreno and Lozano, 2014; Yang et al., 2021; Kim et al., 2024) and player level (Cooper et al., 2009, 2011; Radovanović et al., 2013, 2014).

Conventional DEA, however, treats the production process as a black box. For a basketball player, this abstraction is costly: offensive and defensive performance are not sequential stages but occur simultaneously, with the same resource — court time — allocated to both. A model blind to this parallel structure cannot separate the contribution of each dimension to overall efficiency.

Network DEA addresses this by opening the black box. The framework of Färe and Grosskopf (2000), extended by Tone and Tsutsui (2009) to a non-homogeneous slack-based formulation, allows each stage its own input and output set while sharing a common resource. The parallel structure maps naturally onto basketball: playing time enters both offensive and defensive stages simultaneously, and each is evaluated independently before aggregation into an overall score.

A further issue concerns zero-valued outputs. Guards, forwards, and centres differ systematically in blocked shots, and a non-negligible share of any large sample will record blocks per game of exactly zero. In the standard SBM denominator, a near-zero output value causes the efficiency score to collapse regardless of performance on every other metric — a pathology of the model, not a finding about the player. Following Tone (2001) and Portela et al. (2004), we exclude zero-valued output terms from the SBM denominator. The practical effect is substantial: the share of player-seasons receiving a defensive efficiency score below 0.40 falls from 16.7 percent under the uncorrected model to under one percent after correction.

The Turkish Basketball League is a fitting setting for this analysis. The league draws players with EuroLeague experience and operates under foreign-player quotas that produce roster heterogeneity comparable to other mid-tier European leagues, yet it has received no individual-level frontier efficiency analysis in the published literature. The three-season panel covers 2023–24 through 2025–26, with 100 players per season selected on minimum playing-time and games-played thresholds.

The paper proceeds as follows. Section 2 reviews the DEA literature in sports and parallel network DEA. Section 3 develops the methodological framework. Section 4 describes the data and reports results. Sections 5 and 6 discuss and conclude.

Literature Review

DEA in Sports: An Overview

Sports DEA research evolved from early single-stage models — in which teams or players convert wage expenditure and playing time into wins — toward increasingly articulated representations of the production process. A central limitation of the black-box specification is that it assigns an efficiency score to the DMU as a whole without identifying which sub-process

drives underperformance. For team-level analysis this matters; for individual player analysis, where offensive and defensive activity occur simultaneously rather than sequentially, it is decisive. Cross-sport comparisons have proven useful for isolating institutional effects: Lee (2009) found that the Korean Basketball League recorded the highest mean efficiency among three professional sports (74.9%), attributing this partly to the salary cap, while Zhang et al. (2023) examined sports resource utilisation across China's 31 provinces using SBM-DEA and the Malmquist Index, finding a national average efficiency of 0.6307 with technology change — not efficiency catch-up — driving productivity growth.

Individual Player Efficiency in Basketball

The DEA literature on basketball players begins with Cooper et al. (2009), who addressed the weight-flexibility problem directly: standard DEA assigns each DMU its most favourable weights, potentially concentrating the entire score on a single statistic. Their procedure guarantees a full profile of non-zero multipliers, enabling meaningful cross-player comparison. Cooper et al. (2011) extended this through a cross-efficiency approach rewarding balanced performance across all dimensions. Radovanović et al. (2013, 2014) combined DEA with distance-based analysis and machine learning on NBA guards, demonstrating that methodological choice carries substantive consequences for ranking. Yesilyurt (2014) established variable selection as a first-order methodological decision by comparing salary-based, statistics-based, and hybrid input specifications across 401 NBA players. Chen et al. (2017) corrected for the bounded-integer nature of basketball statistics, while Masoumzadeh et al. (2016) contributed a model for systems without explicit inputs applicable to player evaluation.

Team Efficiency and Organisational Performance

Team-level studies connect production-side efficiency to financial and competitive outcomes. Kim et al. (2024) found that operational efficiency contributes significantly to NBA franchise value, and Chatzistamoulou et al. (2022) showed that salary cap implementation narrowed the efficiency gap between high- and low-payroll clubs. At the domestic level, Tunca and Gök (2012) applied SBM-DEA and super-efficiency analysis to TBL clubs across three seasons (2008–11), identifying Efes Pilsen and Fenerbahçe as consistently dominant franchises and demonstrating that frontier-based rankings closely but imperfectly mirror league standings. The collective implication is that player and team efficiency scores capture information not visible in raw output totals, but team-level analyses cannot decompose offensive and defensive contributions at the individual level — the gap this study addresses.

Network DEA and the Internal Structure of Production

Network DEA opens the production black box by modelling the DMU as a system of interlinked sub-processes (Färe & Grosskopf, 2000; Tone & Tsutsui, 2009). Lewis (2014) applied this to Major League Baseball, separating front-office and on-field operations. Moreno and Lozano (2014) brought NDEA to basketball with the most structurally ambitious application in the literature, modelling each NBA team as a five-stage network and demonstrating that the network model's discriminating power substantially exceeds that of a single-stage approach. Villa and Lozano (2018) extended NDEA to the game level with a dynamic model in which quarterly score margins link successive sub-processes. Yang et al. (2021) resolved non-homogeneity at the team level by assigning each DMU an input-output subset consistent with both an atomic and a maximum property. In football, Villa and Lozano (2024) proposed a shared-input integer NDEA linking club wages to market value. The parallel architecture — in which inputs are allocated simultaneously across independent sub-processes rather than sequentially — is the natural representation of individual basketball performance, where offensive and defensive output are produced concurrently from the same minutes.

Undesirable Outputs and Zero-Valued Data

Tone (2004) incorporated undesirable outputs into the SBM objective function by reversing the direction of the relevant

slack. A less discussed but practically significant issue concerns zero-valued outputs. In positionally heterogeneous samples, blocked shots per game equals zero for a non-trivial share of observations. The standard SBM denominator divides each output slack by the observed value; when that value is zero, the term diverges and the efficiency score collapses regardless of performance on other variables. Following Tone (2001) and Portela et al. (2004), this study excludes zero-valued output terms from the denominator, rather than substituting an arbitrary small constant. The practical consequence in the TBL sample is documented in Section 4.

Gap in the Literature

Individual-level DEA analysis of basketball players remains confined almost entirely to the NBA; no published study applies frontier methods to TBL players. The parallel NDEA architecture has not been applied to individual basketball players, where the natural decomposition is between offensive and defensive production sharing a common input — court time. The zero-output correction, while theoretically established, has not been systematically documented in sports DEA with positionally heterogeneous samples. This study addresses all three gaps simultaneously.

Methods

Data Envelopment Analysis and the SBM Model

Data Envelopment Analysis constructs an empirical best-practice frontier from observed input-output data and scores each DMU against that frontier without imposing a functional form or externally determined weights (Charnes et al., 1978; Banker et al., 1984). Early radial models summarise inefficiency as a single proportional scalar, discarding the non-radial slack — residual input excesses and output shortfalls — that persists after proportional adjustment. In a multidimensional performance setting where different statistics contribute unequally to a player's production profile, this omission biases efficiency rankings.

Tone (2001) resolved this through the Slack-Based Measure, which embeds slacks directly in the objective function. The SBM score is units-invariant, strictly monotone in every slack, and bounded on $[0, 1]$; unity requires all slacks to be simultaneously zero. The model is estimated under variable returns to scale, benchmarking each player against peers at a comparable scale of activity. When undesirable outputs are present, Tone (2004) extends the SBM denominator to penalise their excess: turnover slack enters alongside desirable output shortfalls, reducing the defensive efficiency score of players who surrender possession more than frontier peers.

A further refinement concerns zero-valued outputs. Blocked shots equal zero for a non-trivial share of observations; the standard SBM denominator divides each output slack by the observed value, so a zero collapses the efficiency score regardless of performance elsewhere. Following Tone (2001) and Portela et al. (2004), zero-valued output terms are excluded from the denominator entirely. This correction affects 68 observations in the defensive stage and is consequential: without it, 16.7 percent of player-seasons receive a defensive score below 0.40; after correction, fewer than one percent do.

Network DEA and the Parallel Architecture

Standard DEA treats production as a black box. Network DEA opens it by modelling the DMU as a system of interlinked sub-processes (Färe & Grosskopf, 2000; Tone & Tsutsui, 2009). In a serial structure, the first stage's output feeds the second as an intermediate product. In a parallel structure, inputs are allocated simultaneously across independent sub-processes producing distinct outputs. Individual basketball performance is inherently parallel: a player produces offensive and defensive output concurrently from the same minutes — imposing a serial ordering would introduce a causal assumption with no empirical basis. The parallel architecture also accommodates the non-homogeneity between stages: three inputs and four outputs in the offensive stage; one input, four desirable outputs, and one undesirable output in the defensive stage. System

efficiency is a weighted combination of stage scores, with equal weights applied as detailed in Section 3.5.

Notation

The study covers n DMUs per season ($n = 100$), indexed $j = 1, \dots, n$, evaluated under two parallel stages $k \in \{1, 2\}$, where $k = 1$ denotes the offensive stage and $k = 2$ the defensive stage. The offensive stage takes $m_1 = 3$ inputs — minutes per game (**MPG**), field goal attempts (**FGA**), and free throw attempts (**FTA**) — and produces $s_1 = 4$ desirable outputs: points per game (**PPG**), field goals made (**FGM**), free throws made (**FTM**), and offensive rebounds (**ORB**). The defensive stage takes $m_2 = 1$ input — **MPG**, the same shared resource — and produces $s_2 = 4$ desirable outputs: defensive rebounds (**DRB**), assists (**APG**), steals (**SPG**), and blocks (**BPG**), together with $b_1 = 1$ undesirable output, turnovers (**TOV**), which penalises ball-security failures in the spirit of Tone (2004). For the DMU under evaluation, indexed o , observed input and output values are denoted $x_{io}^{(k)}$, $y_{ro}^{(k)}$, and $b_o^{(2)}$; the corresponding quantities for the reference DMU j are $x_{ij}^{(k)}$, $y_{rj}^{(k)}$, and $b_j^{(2)}$. Intensity weights $\lambda_j^{(k)} \geq 0$ span the production possibility set, and $\varepsilon > 0$ is a small non-Archimedean constant that prevents degenerate solutions.

Stage-Level SBM Models

Each stage is linearised via the Charnes–Cooper transformation. Define $t^{(k)} = 1/D^{(k)}$, where $D^{(k)}$ is the denominator of the SBM ratio for stage k , and let $S_i^{x(k)} = t^{(k)} s_i^{x(k)}$, $S_r^{y(k)} = t^{(k)} s_r^{y(k)}$, and $S^{b(2)} = t^{(2)} s^{b(2)}$ denote the scaled slack variables.

Stage 1: Offensive efficiency. The linear programme solved for DMU o is:

$$\min t^{(1)} - \frac{1}{m_1} \sum_{i=1}^{m_1} \frac{S_i^{x(1)}}{x_{io}^{(1)}} \quad (1)$$

subject to the normalisation constraint:

$$t^{(1)} + \frac{1}{s_1} \sum_{r=1}^{s_1} \frac{S_r^{y(1)}}{y_{ro}^{(1)}} = 1 \quad (2)$$

input feasibility constraints:

$$\sum_{j=1}^n \lambda_j^{(1)} x_{ij}^{(1)} = t^{(1)} x_{io}^{(1)} - S_i^{x(1)}, i = 1, \dots, m_1 \quad (3)$$

output feasibility constraints:

$$\sum_{j=1}^n \lambda_j^{(1)} y_{rj}^{(1)} = t^{(1)} y_{ro}^{(1)} + S_r^{y(1)}, r = 1, \dots, s_1 \quad (4)$$

the VRS convexity constraint:

$$\sum_{j=1}^n \lambda_j^{(1)} = t^{(1)} \quad (5)$$

and non-negativity: $\lambda_j^{(1)}, S_i^{x(1)}, S_r^{y(1)} \geq 0, t^{(1)} \geq \varepsilon$. The Charnes–Cooper transformation renders Eq. (1)–(6) a standard linear programme. The offensive efficiency score is then recovered as:

$$\rho_1 = \frac{t^{(1)} - \frac{1}{m_1} \sum_{i=1}^{m_1} \frac{S_i^{x(1)}}{x_{io}^{(1)}}}{t^{(1)} + \frac{1}{s_1} \sum_{r=1}^{s_1} \frac{S_r^{y(1)}}{y_{ro}^{(1)}}} \quad (6)$$

Stage 2: Defensive efficiency with undesirable output. The corresponding programme is:

$$\min t^{(2)} - \frac{1}{m_2} \sum_{i=1}^{m_2} \frac{S_i^{x(2)}}{x_{io}^{(2)}} \quad (7)$$

subject to the normalisation constraint, which now incorporates both desirable and undesirable output slacks:

$$t^{(2)} + \frac{1}{s_2 + b_1} \left(\sum_{r=1}^{s_2} \frac{S_r^{y(2)}}{y_{ro}^{(2)}} + \frac{S^{b(2)}}{b_o^{(2)}} \right) = 1 \quad (8)$$

input feasibility:

$$\sum_{j=1}^n \lambda_j^{(2)} x_{ij}^{(2)} = t^{(2)} x_{io}^{(2)} - S_i^{x(2)}, i = 1, \dots, m_2 \quad (9)$$

desirable output feasibility:

$$\sum_{j=1}^n \lambda_j^{(2)} y_{rj}^{(2)} = t^{(2)} y_{ro}^{(2)} + S_r^{y(2)}, r = 1, \dots, s_2 \quad (10)$$

undesirable output constraint, where the sign is reversed to penalise excess turnovers:

$$\sum_{j=1}^n \lambda_j^{(2)} b_j^{(2)} = t^{(2)} b_o^{(2)} - S^{b(2)} \quad (11)$$

VRS convexity:

$$\sum_{j=1}^n \lambda_j^{(2)} = t^{(2)} \quad (12)$$

and non-negativity: $\lambda_j^{(2)}, S_i^{x(2)}, S_r^{y(2)}, S^{b(2)} \geq 0$, with the additional bound $S^{b(2)} \leq t^{(2)} b_o^{(2)}$ to ensure the scaled slack remains feasible. Eq. (12) states that the reference set can produce no more turnovers than the evaluated player after scaling — excess turnovers above the frontier level are captured in $S^{b(2)}$ and contribute positively to the denominator in Eq. (9), thereby reducing the efficiency score. The defensive efficiency score is:

$$\rho_2 = \frac{t^{(2)} - \frac{1}{m_2} \sum_{i=1}^{m_2} \frac{S_i^{x(2)}}{x_{io}^{(2)}}}{t^{(2)} + \frac{1}{s_2 + b_1} \left(\sum_{r=1}^{s_2} \frac{S_r^{y(2)}}{y_{ro}^{(2)}} + \frac{S^{b(2)}}{b_o^{(2)}} \right)} \quad (13)$$

Both Eq. (6) and Eq. (13) are bounded on $[0, 1]$. A score of $\rho_k = 0.70$ means the player reaches 70 percent of the maximum output that frontier peers extract from equivalent inputs; the remaining 30 percent represents slack-identifiable waste.

Overall System Efficiency

Following the non-homogeneous parallel NDEA framework of Tone and Tsutsui (2009), overall system efficiency is defined as a weighted average of stage efficiencies. Since no prior basis exists for favouring offensive over defensive performance or vice versa, equal weights are applied:

$$\rho = \frac{\rho_1 + \rho_2}{2} \quad (14)$$

Since $\rho_1, \rho_2 \in [0, 1]$, Eq. (14) guarantees $\rho \in [0, 1]$. Full system efficiency ($\rho = 1$) requires $\rho_1 = \rho_2 = 1$ simultaneously, meaning all slacks must be zero in both stages at once. This joint condition is structurally more demanding than single-stage full efficiency and is one reason parallel NDEA typically exhibits greater discriminating power than a conventional black-box model (Moreno & Lozano, 2014).

Estimation Procedure

The 100 DMUs in each season are solved independently, so each player is benchmarked exclusively against contemporaries from the same season. Within-season reference sets are standard in cross-sectional DEA and prevent shifts in the overall player pool between seasons from contaminating individual efficiency scores. For each DMU o , Eq. (1)–(6) and Eq. (7)–(13) are solved as two separate linear programmes; the resulting stage scores are combined via Eq. (14). The models are implemented and solved in LINGO 19.0 and Microsoft Excel. For player-season observations in which a desirable output takes a value of zero — most notably blocked shots per game — the corresponding slack-to-output ratio is excluded from the SBM denominator following Tone (2001) and Portela et al. (2004), rather than evaluated at an arbitrarily small constant. This correction affects [68] observations in the defensive stage and prevents score distortion for positionally specialised players. All 300 optimisation problems return Optimal status; no infeasible solutions were encountered. The maximum deviation from the identity $\rho = 0.5\rho_1 + 0.5\rho_2$ across the full dataset is 5×10^{-5} , confirming numerical consistency throughout.

Application

Scope and Data

The dataset covers three consecutive TBL seasons: 2023–24, 2024–25, and 2025–26. Each season's sample comprises the 100 players with the highest on-court production, subject to a minimum of 17.0 minutes per game; players below this threshold generate per-game averages too volatile to anchor a meaningful efficiency benchmark. The result is 100 DMUs per season and 300 in total. Full player-season records are reported in Appendix Table 1. Season-level and pooled descriptive statistics are presented in Table 1.

For the offensive stage, inputs are minutes per game (MPG), field goal attempts (FGA), and free throw attempts (FTA);

outputs are points (PPG), field goals made (FGM), free throws made (FTM), and offensive rebounds (ORB). As Table 1 shows, mean PPG narrowed from 12.81 in 2023–24 to 11.40 in 2025–26 alongside a decline in mean MPG from 26.79 to 24.26, reflecting a consistent contraction in individual scoring load. The pooled range — 7.7 to 23.3 for PPG and 17.0 to 36.9 for MPG — confirms substantial heterogeneity even within the top-100 group.

For the defensive stage, the sole input is MPG. Total playing time serves as the best available proxy for defensive capacity, a convention with broad support in the literature (Cooper et al., 2009; Moreno & Lozano, 2014). Defensive outputs are defensive rebounds (DRB), assists (APG), steals (SPG), and blocks (BPG). Turnovers (TOV) enter as an undesirable output consistent with Tone (2004). The pooled median BPG of 0.20 reflects that shot-blocking is a positionally concentrated action across the broader player pool, motivating the zero-output correction described in Section 3.1. All data were sourced from the TBF official statistical portal and the BSL statistics platform (bsl.tblstat.net) as per-game averages.

Table 1.
Descriptive Statistics — Season-Level and Pooled Sample

Variable	Role	2023–24	2024–25	2025–26	Pooled (n=300)
MPG	Input (Off+Def)	26.79 (4.02)	25.11 (4.03)	24.26 (3.60)	25.39 (4.02)
FGA	Input (Off)	9.45 (2.04)	8.78 (2.21)	8.35 (1.93)	8.86 (2.10)
FTA	Input (Off)	3.05 (1.41)	2.91 (1.44)	2.94 (1.30)	2.97 (1.38)
PPG	Output-Off	12.81 (2.80)	12.08 (2.76)	11.40 (2.45)	12.09 (2.73)
FGM	Output-Off	4.55 (0.97)	4.25 (1.00)	3.94 (0.82)	4.25 (0.96)
FTM	Output-Off	2.34 (1.11)	2.26 (1.16)	2.29 (1.08)	2.30 (1.12)
ORB	Output-Off	1.09 (0.84)	1.03 (0.81)	1.02 (0.80)	1.04 (0.81)
DRB	Output-Def	3.04 (1.15)	2.75 (1.03)	2.66 (0.99)	2.82 (1.07)
APG	Output-Def	2.84 (1.62)	2.80 (1.64)	2.60 (1.71)	2.75 (1.66)
SPG	Output-Def	0.86 (0.37)	0.84 (0.34)	0.86 (0.35)	0.85 (0.36)
BPG	Output-Def	0.31 (0.38)	0.26 (0.31)	0.26 (0.30)	0.28 (0.33)
TOV	Undesirable	1.64 (0.62)	1.57 (0.68)	1.58 (0.64)	1.60 (0.65)

Note: Values are Mean (SD). n = 100 per season. Pooled column shows mean (SD) across all 300 observations. Off = offensive stage; Def = defensive stage.

Results

Overall Efficiency Scores and Distribution

Efficiency scores from the parallel Network SBM-DEA model are summarised by season in Table 3. Across the pooled sample of 300 player-season observations, the mean overall efficiency is 0.7074, indicating that TBL players in the top-100 tier operate at roughly 71 percent of the attainable frontier given their observed inputs — an inefficiency margin of around 29 percent that survives radial adjustment and represents genuine slack under the SBM formulation.

Considerable variation across seasons is evident. The 2024–25 season records the highest mean overall efficiency at 0.7419 and the largest count of fully efficient DMUs at 18, while 2023–24 and 2025–26 return means of 0.6957 and 0.6846 respectively, with 11 and 11 fully efficient observations each. The distribution across five performance bands (Table 2, Panel B) shows that 56 of 300 DMUs — 19 percent — fall in the efficient or near-efficient band ($\theta \geq 0.90$), while 11 observations — 4 percent — fall below the 0.40 threshold, reflecting genuine output shortfalls across non-zero variables rather than model distortion; the zero-output correction documented in Section 3.1 prevents BPG = 0 observations from collapsing to zero but does not eliminate low efficiency scores driven by weak performance on the remaining defensive outputs. Figure 1 presents the season-by-season distribution of overall efficiency scores as a comparative box plot.

When offensive and defensive stages are examined separately, a structural asymmetry emerges that persists across all

three seasons. Mean offensive efficiency ranges from 0.7317 in 2023–24 to 0.7471 in 2025–26, while mean defensive efficiency spans a lower but overlapping band of 0.6222 to 0.7424. The pooled gap between the two stages averages 0.0653; 100 of 300 player-season observations show offensive efficiency exceeding defensive efficiency by more than 0.20. The asymmetry is most pronounced in 2025–26, where the gap reaches 0.1249, coinciding with the lowest mean playing time of the three seasons (24.26 minutes, down from 26.79 in 2023–24). Figure 2 illustrates the seasonal trajectory of offensive and defensive efficiency side by side.

Table 2.

Season-Level Network SBM-DEA Efficiency Results and Distribution across Efficiency Bands

Season							Efficiency Band		
Season	θ Overall	SD	Min	Median	Max	Efficient (n)	θ Offensive	θ Defensive	Δ (Off – Def)
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2023–24	0.6957	0.1873	0.2984	0.6963	1.0000	11	0.7317	0.6597	+0.0719
2024–25	0.7419	0.1891	0.3516	0.7429	1.0000	18	0.7415	0.7424	–0.0009
2025–26	0.6846	0.1781	0.3317	0.6935	1.0000	11	0.7471	0.6222	+0.1249
Overall	0.7074	0.1859	0.2984	0.7105	1.0000	40	0.7401	0.6748	+0.0653
Band	Criterion n	Total (n)	2023–24	2024–25	2025–26	Mean θ	Mean θ_{off}	Mean θ_{def}	
Very Low	$\theta < 0.40$	11	3	3	5	0.3538	0.3762	0.3314	
Low	$0.40 \leq \theta < 0.60$	81	28	22	31	0.5054	0.5294	0.4813	
Moderate	$0.60 \leq \theta < 0.75$	85	32	26	27	0.6785	0.7338	0.6232	
High	$0.75 \leq \theta < 0.90$	67	21	22	24	0.8176	0.8595	0.7758	
Efficient	$\theta \geq 0.90$	56	16	27	13	0.9811	0.9828	0.9795	
Total		300	100	100	100				

Note: Panel A — Efficient = $\theta_{overall} \geq 0.9999$. $n = 100$ per season. Δ = mean offensive minus mean defensive efficiency. Panel B — Percentage contributions calculated within each season.

Figure 1.

Season-wise Distribution of Overall Efficiency ($\theta_{overall}$)

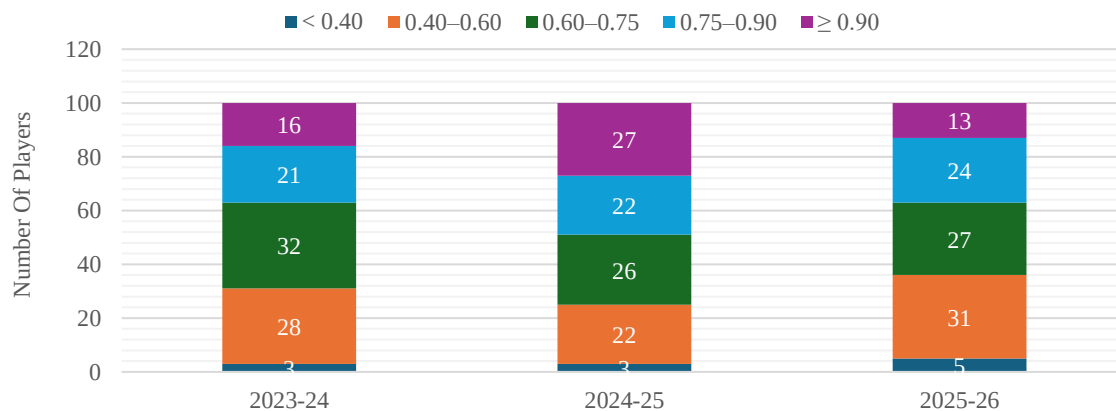
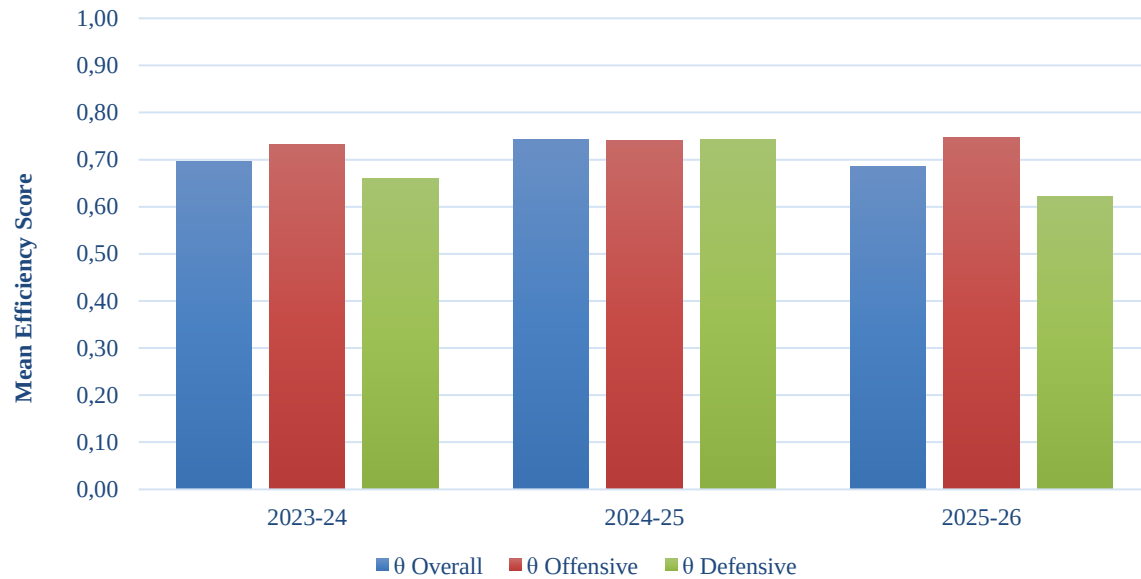


Figure 2.
Offensive versus Defensive Efficiency Across Seasons



Profile of Fully Efficient Players

Full efficiency ($\theta = 1.000$) was achieved by 40 player-season observations: 11 in 2023–24, 18 in 2024–25, and 11 in 2025–26 (Table 3). The frontier is heterogeneous by design: under VRS, Enes Taşkıran (MPG = 17.0, PPG = 8.8) and Nathaniel Mason (MPG = 36.9, PPG = 19.6) both sit on the 2023–24 frontier despite operating at radically different scales. In 2024–25, Javon Freeman-Liberty achieves full efficiency in a single-game observation and is excluded from substantive interpretation. Sertaç Sanlı is the only player to reach full efficiency in two consecutive seasons (2023–24 and 2024–25).

Table 3.
Fully Efficient Players by Season ($\theta_{overall} = 1.000$)

Player	Team	GP	MPG	PPG	FGM	FTM	ORB	DRB	APG	SPG	BPG	TOV
2023–24 (n = 11)												
Austin Wiley	TOF	24	27.4	15.2	5.8	3.7	3.3	6.8	0.8	0.6	1.9	1.2
Daniel Oturu	MERK	10	32.9	20.3	7.5	5.3	3.5	6.1	1.4	1.1	1.6	3.5
Emanuel Terry	MANI	32	28.7	12.8	5.0	2.8	2.6	5.9	1.4	1.1	0.7	1.4
Enes Taşkıran	DBI	13	17.0	8.8	3.1	1.0	0.4	1.4	1.2	0.6	0.1	1.1
Erick McCollum	PIN	33	26.6	19.8	6.2	5.4	0.8	2.3	5.8	1.2	0.3	2.4
Josh Carlton	DBI	14	19.2	9.7	4.2	1.3	2.7	3.6	0.6	0.9	1.0	1.0
Mahir Ağva	SOC	32	17.4	9.0	3.4	2.2	1.8	2.8	1.2	0.6	0.3	0.8
Marcquise Reed	DEM	30	29.7	21.1	7.2	5.0	0.9	3.2	3.7	2.0	0.1	2.3
Marko Pečarski	MERK	24	25.1	11.1	4.5	1.0	2.4	3.2	0.8	0.3	0.3	0.5
Nathaniel Mason	MERK	22	36.9	19.6	6.8	3.6	0.5	2.5	7.1	1.3	0.0	3.2
Sertaç Sanlı	FEN	37	18.1	9.1	3.5	1.2	1.1	3.0	1.1	0.4	0.6	0.8
2024–25 (n = 18)												
Arturs Zagars	FEN	22	17.6	8.4	2.4	2.5	0.4	0.9	2.9	0.9	0.0	1.7
Berk Uğurlu	BES	41	23.5	8.3	3.3	0.6	0.6	1.5	3.4	0.7	0.0	0.5
Braian Angola-Rodas	TUR	24	24.6	13.4	3.7	4.2	0.7	4.0	4.8	0.9	0.1	1.7
Ebuka Izundu	GAL	30	19.0	10.7	4.2	2.2	3.0	3.4	0.6	0.8	0.7	0.9
Egemen Güven	MERK	14	19.1	8.4	3.9	0.6	0.9	3.1	1.5	0.3	0.6	0.7
Erick McCollum	PIN	12	27.2	16.0	4.8	4.4	1.0	1.2	5.2	0.8	0.5	1.7

Gabriel Olaseni	MER	32	26.7	12.7	4.7	3.3	3.0	5.4	1.3	0.6	0.5	2.0
Jaime Echenique	SOC	29	17.2	11.3	3.9	3.6	2.6	2.4	0.8	0.4	0.7	1.2
James Webb III	PIN	12	30.1	15.3	5.3	1.9	1.8	4.9	1.5	2.0	0.4	1.0
Javon Freeman-Liberty*	MANI	1	28.7	9.0	4.0	0.0	0.0	5.0	2.0	1.0	0.0	0.0
Jo Acuil	MANI	21	26.4	17.2	6.6	3.9	2.6	4.4	1.0	0.8	1.0	1.8
Kris Bankston	TOF	33	21.1	9.2	3.9	1.4	2.0	3.0	1.0	0.9	0.8	0.8
Marko Simonovic	BAHC	34	17.3	8.3	3.1	1.2	1.6	3.0	1.0	0.6	0.3	0.9
Martin Krampelj	YAL	29	23.3	12.4	4.3	2.9	1.3	3.7	1.0	1.4	0.4	1.0
Martynas Sajus	DEM	32	24.8	12.1	4.1	3.9	2.5	3.2	1.4	0.8	1.3	1.6
Melih Mahmutoglu	FEN	39	19.6	9.6	3.4	0.5	0.2	1.0	0.7	0.2	0.0	0.4
Rodrigue Beaubois	EFE	13	18.6	11.2	4.1	0.8	0.1	1.9	2.1	0.7	0.8	0.7
Sertaç Sanlı	FEN	29	17.6	8.3	2.8	1.8	1.4	2.9	1.0	0.2	0.4	0.6
2025–26 (n = 11)												
Anthony Cowan	MER	29	26.7	14.9	3.7	5.3	0.2	1.4	6.8	0.8	0.1	2.8
B.J. Boston Jr.	FEN	19	17.3	8.4	2.9	1.7	1.0	1.7	0.7	0.4	0.1	0.7
Brandon Childress	BURS	30	29.9	14.9	4.3	4.5	0.2	2.4	6.8	1.8	0.0	3.3
Brice Dessert	EFE	26	19.1	8.5	3.5	1.4	1.2	2.0	0.5	0.3	1.3	0.9
Christian Bishop	PIN	17	19.3	10.6	3.8	3.1	1.4	3.3	0.9	1.2	0.1	1.2
Ismael Kamagate	BES	20	17.6	8.4	3.2	2.1	2.8	3.1	0.4	0.6	1.1	0.7
Maozinho Pereira	MANI	26	24.4	11.7	5.0	1.1	2.2	3.8	1.2	1.4	1.6	0.9
Ronald March Jr.	MER	30	18.2	9.5	3.6	0.8	0.7	2.5	1.3	1.5	0.4	1.2
Talen Horton-Tucker	FEN	31	21.1	13.2	4.4	3.4	1.0	2.5	3.0	1.1	0.6	1.9
Trevion Williams	BAHC	34	23.0	10.4	4.6	1.1	3.1	6.0	2.5	0.5	0.3	1.7
Joseph Girard III	TRA	10	17.6	9.7	3.4	0.3	0.3	1.0	2.5	0.9	0.0	1.5

Note: All values are per-game averages. * Javon Freeman-Liberty (2024–25, GP = 1) satisfies the VRS frontier conditions given the single-observation reference set but does not constitute a meaningful benchmark; his observation is retained in the dataset to avoid sample distortion but is excluded from all substantive interpretation and does not enter the super-efficiency analysis.

Team-Level Efficiency

Clustering player efficiency scores by club reveals a clear hierarchical structure across the league. As Table 4 shows, Fenerbahçe (FEN) leads with a mean overall efficiency of 0.8306 — well ahead of second-placed Anadolu Efes (EFE) at 0.7503 and third-placed Galatasaray (GAL) at 0.7424. The team-level offensive–defensive profiles diverge considerably. Fenerbahçe posts the highest offensive efficiency in the league (0.8786) and also the highest defensive efficiency (0.7825, ahead of Efes at 0.7074). A contrasting pattern appears at Trabzonspor (TRA): a comparatively strong offensive rating (0.7847) coexists with the league's markedly lower defensive efficiency (0.6575), suggesting a roster built around scoring rather than defensive balance. Türk Telekom (TUR), by contrast, presents the most balanced profile in the sample, with offensive and defensive efficiencies of 0.6994 and 0.7243, respectively — with its two stages essentially level, unlike the league-average gap of 0.0653.

At the foot of the table, Çağdaş Bodrum (CAG, 0.6029) records the lowest overall efficiency, weak across both dimensions, and places no player on the full efficient frontier across the three seasons covered.

Table 4.
Team-Level Efficiency Results (ranked by $\theta_{overall}$)

Rank	Team	Obs. (n)	θ Overall	θ Offensive	θ Defensive	Efficient (n)
1	FEN	23	0.8306	0.8786	0.7825	6
2	EFE	23	0.7503	0.7932	0.7074	2
3	GAL	15	0.7424	0.8000	0.6848	1
4	MER	11	0.7405	0.7780	0.7030	3

5	MANI	21	0.7374	0.7693	0.7054	4
6	MERK	21	0.7258	0.7680	0.6836	4
7	PIN	21	0.7223	0.7850	0.6596	4
8	TRA	6	0.7211	0.7847	0.6575	1
9	DEM	14	0.7127	0.6985	0.7269	2
10	TUR	17	0.7118	0.6994	0.7243	1
11	BES	18	0.6777	0.7233	0.6320	2
12	DBI	16	0.6774	0.6714	0.6833	2
13	BAHC	18	0.6748	0.7467	0.6029	2
14	ENEN	7	0.6727	0.6172	0.7283	0
15	SAM	6	0.6694	0.6505	0.6882	0
16	SOC	17	0.6607	0.7380	0.5834	2
17	TOF	17	0.6445	0.6447	0.6444	2
18	BURS	19	0.6352	0.6606	0.6098	1
19	YAL	5	0.6210	0.6620	0.5800	1
20	CAG	5	0.6029	0.6140	0.5918	0

Note: Obs. = total player-season observations linked to that club. Efficient = $\theta_{\text{overall}} \geq 0.9999$.

Panel Analysis — Players Appearing in All Three Seasons

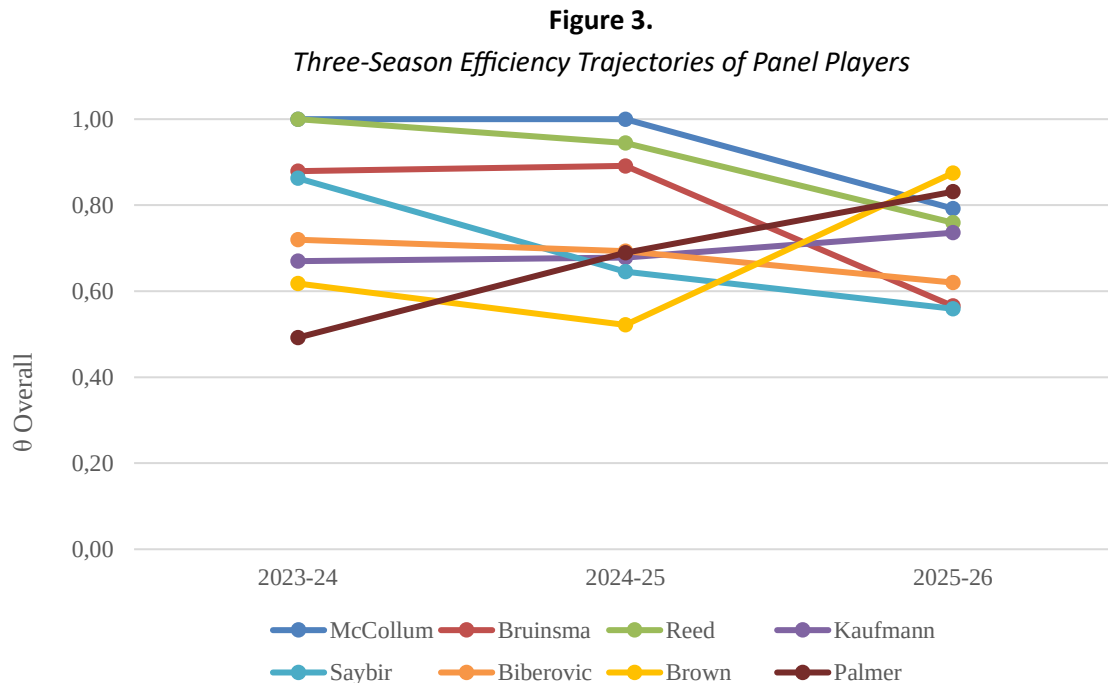
Sixteen players appear in the top-100 sample in every season, enabling a longitudinal comparison of individual efficiency trajectories. Table 5 ranks these players by three-season average efficiency, and Figure 3 traces each player's seasonal path as a line chart.

Errick McCollum is the standout figure: scores of 1.000, 1.000, and 0.7922 across consecutive seasons yield a three-season average of 0.9307, the highest in the panel. His ability to sustain frontier performance across different team environments — he represented three clubs over the period — points to a robustness in efficiency that is independent of squad context. James Palmer Jr. and Kyle Allman Jr. trace the panel's steepest upward trajectories: Palmer advances from 0.4921 to 0.8312, while Allman climbs from a remarkable low of 0.0584 to 0.8619, the sharpest single-panel improvement observed. Both progressions are consistent with a learning-curve effect, whereby extended TBL experience translates into improved input-output management over time. David Efiyanayi represents the opposite case: a sharp collapse from 0.6981 in 2023–24 to 0.1602 in 2024–25, coinciding with a team transfer, illustrates how the adaptation cost of a mid-career move can register as a severe but potentially temporary efficiency shock. Evan Bruinsma and Yiğitcan Saybir both show a persistent downward trend — from 0.8788 and 0.8627 in 2023–24 to 0.5655 and 0.5592 in 2025–26 — suggesting that their initial efficiency advantage eroded as the reference set evolved around them.

Table 5.
Panel Players — Three-Season Efficiency Comparison

Player	2023–24	2024–25	2025–26	Mean θ	Trend
Errick McCollum	1.0000	1.0000	0.7922	0.9307	Declining
Evan Bruinsma	0.8788	0.8914	0.5655	0.7786	Variable
Marcquise Reed	1.0000	0.9447	0.7593	0.9013	Declining
Alexander Perez Kaufmann	0.6699	0.6779	0.7359	0.6946	Stable
Yiğitcan Saybir	0.8627	0.6455	0.5592	0.6891	Declining
Tarik Biberovic	0.7197	0.6928	0.6201	0.6775	Declining
Anthony Brown	0.6181	0.5216	0.8748	0.6715	Variable
James Palmer Jr.	0.4921	0.6892	0.8312	0.6708	Improving
Shane Larkin	0.7494	0.6137	0.6090	0.6574	Declining
Tyler Cavanaugh	0.6151	0.5691	0.6929	0.6257	Stable

Markel Starks	0.8195	0.8375	0.4379	0.6983	Variable
Kyle Allman Jr.	0.8211	0.6161	0.8619	0.7663	Variable
Yannick Franke	0.5337	0.7110	0.7649	0.6699	Improving
Jonah Mathews	0.3920	0.7351	0.3506	0.4926	Variable
David Efanayi	0.6981	0.3548	0.5093	0.5207	Variable
Pako Cruz	0.6231	0.7701	0.8073	0.7335	Improving



Slack Analysis — Sources of Inefficiency

Slack analysis across the 260 inefficient DMUs ($\theta < 0.9999$) decomposes overall inefficiency into its variable-level components. Results are reported in Table 6.

In the offensive stage, by far the largest slack belongs to MPG (mean = 2.034), accounting for 47.6 percent of total offensive slack. This implies that, on average, inefficient players carry approximately two minutes of playing time per game that yields no marginal improvement in offensive output relative to what their frontier peers achieve with the same resources. The second largest offensive slack is ORB (0.970, 22.7 percent), pointing to a pronounced gap in offensive rebounding productivity. FGA accounts for 15.1 percent of offensive slack, suggesting that shot selection — the conversion efficiency of attempts into made field goals and points — is the third most important source of offensive underperformance. By contrast, FTA slack (0.3 percent) and FTM slack (1.0 percent) are negligible, indicating that free-throw generation and conversion lie near frontier levels for most players.

In the defensive stage, MPG again dominates (1.104, 36.0 percent), followed by DRB (0.802, 26.1 percent) and BPG (0.563, 18.4 percent). The large defensive MPG slack echoes the offensive finding: a portion of each player's floor time is not translating into measurable defensive output. The relatively low slack values for APG (0.157, 5.1 percent) and TOV (0.216, 7.0 percent) indicate that playmaking and ball security are closer to efficient benchmarks — turnovers, while penalised as an undesirable output, are not the primary driver of defensive shortfall in this sample.

Table 6.
Mean Slack Values and Proportional Contribution (Inefficient DMUs, $n = 261$)

Stage	Variable	Role	Mean Slack	% Contribution
Offensive	MPG	Input	2.0345	47.6%
	FGA	Input	0.6442	15.1%
	FTA	Input	0.0109	0.3%
	PPG	Output	0.2336	5.5%
	FGM	Output	0.3340	7.8%
	FTM	Output	0.0422	1.0%
	ORB	Output	0.9704	22.7%
Defensive	MPG	Input	1.1042	36.0%
	DRB	Output	0.8016	26.1%
	APG	Output	0.1573	5.1%
	SPG	Output	0.2278	7.4%
	BPG	Output	0.5633	18.4%
	TOV	Undesirable	0.2156	7.0%

Note: Percentage contributions are calculated within each stage. Slack values are expressed in the original units of each variable. FGA slack is reported for completeness but is not interpreted independently, as FGA values were reconstructed from season-average field goal percentages, introducing near-perfect collinearity with FGM (see Section 5, Limitations).

Super-Efficiency Analysis

Standard SBM assigns $\theta = 1.000$ to all 40 fully efficient DMUs, leaving them indistinguishable. Applying the super-efficiency model of Tone (2002) — in which each efficient DMU is re-evaluated against the reference set with itself excluded — allows scores to exceed unity and produces a complete ranking within the frontier. Only DMUs achieving super-efficiency greater than unity in both stages simultaneously receive an overall score; DMUs for which the defensive or offensive programme is infeasible in the enlarged input space are excluded to preserve consistency with the parallel NDEA structure. Of the 40 fully efficient DMUs, only a small number yield a valid overall super-efficiency score under the corrected model, so the measure provides a partial, discriminating ranking rather than a complete ordering of the frontier.

In 2023–24, Mahir Ağva (SOC, $SE = 1.2631$) leads, driven by the highest offensive super-score in the dataset ($SE_{off} = 1.4307$) — a notable result for a player averaging 17.4 minutes and 9.0 points, suggesting his per-minute output profile is distinctively positioned relative to peers. Errick McCollum (PIN, 1.0881) and Sertaç Sanlı (FEN, 1.0650) follow. In 2024–25, Izundu (1.1349) and Simonović (1.0922) head the corrected super-efficiency group, while the remaining efficient units yield no finite overall super-score. That so few efficient units admit a finite overall super-score reinforces the point above: under the corrected model super-efficiency discriminates among a subset of the frontier rather than ranking it in full.

Robustness and Sensitivity Analysis

To establish that the findings do not depend on incidental modelling choices, three sensitivity analyses were conducted on the corrected model. The first concerns the minimum participation threshold. Because the sample includes a small number of very low-appearance observations, the model was re-estimated on the subset of players with at least ten games played. This removes three observations, including the single-game case, and leaves the efficiency ordering essentially unchanged: the Spearman rank correlation between the restricted and full-sample scores is 0.9996, and the pooled mean shifts only from 0.7074 to 0.7053. Raising the threshold to fifteen games removes forty-three observations yet still preserves the ordering at a rank correlation of 0.964. Low-appearance observations therefore do not drive the results.

The second analysis addresses the equal weighting of the offensive and non-scoring stages in the overall score. The

offensive weight was varied across the range 0.30 to 0.70. Player rankings remain highly stable throughout, with Spearman correlations between 0.94 and 1.00 relative to the equal-weighted baseline; the top-twenty players are identical in every specification, the fully efficient set is invariant, and the club ordering is preserved at correlations of 0.92 or above, with Fenerbahçe and Anadolu Efes occupying the top two positions in every case. The equal-weighting convention is thus a transparent choice rather than a determinant of the conclusions.

The third analysis examines the near-collinearity between field goals attempted, which is reconstructed from shooting percentage, and field goals made. Re-estimating the offensive stage without field goals attempted yields offensive scores that correlate with the baseline at 0.93 and overall scores at 0.98. The reconstructed shooting variable therefore does not distort the efficiency estimates.

Taken together, the three checks indicate that the central finding — a moderate, season-dependent asymmetry in which offensive efficiency exceeds non-scoring efficiency on average — is robust to the participation threshold, the stage weighting, and the treatment of the shooting inputs.

Discussion and Conclusion

The pooled mean overall efficiency of 0.7074 indicates that TBL top-100 players operate at roughly 71 percent of the attainable frontier — a margin consistent with Zhang et al. (2023), who report 0.6307 for Chinese provincial sports systems, and with the sub-unity team efficiencies Moreno and Lozano (2014) document for NBA clubs under a comparable network specification.

The most consistent finding is the structural asymmetry between offensive and defensive efficiency. The pooled offensive mean (0.7401) exceeds the defensive mean (0.6748) on average, with the two stages essentially balanced in 2024/25 and the gap widest at 0.1249 in 2025–26 as mean playing time fell to its lowest point across the three seasons (24.26 minutes). Slack decomposition reveals that unused playing time dominates both stages — 47.6 percent of offensive slack and 36.0 percent of defensive slack — pointing to excess playing time relative to the estimated frontier rather than technical skill deficiency as the primary source of inefficiency. The offensive-defensive asymmetry is consistent with the incentive literature's argument that defensive effort is less observable and therefore less rewarded than scoring (Moreno & Lozano, 2014), though direct causal verification lies beyond this study's scope.

These patterns align with and extend the small body of network-DEA research on player efficiency. The closest precedent, Assani et al. (2022), models NBA players through a non-homogeneous parallel DEA network with shared inputs and likewise separates overall, offensive, and defensive efficiency; the present study departs from it by adopting a slack-based rather than a radial measure, by treating turnovers explicitly as an undesirable output, by applying a zero-output correction for positionally specialised players, and by relocating the analysis to a mid-tier European league. The offensive to non-scoring asymmetry documented here is broadly consistent with Ekmekci (2025), who examines defensive contributions in the Turkish Super League, which suggests that the pattern is not an artefact of the present sample.

At the team level, Fenerbahçe leads ($\theta = 0.8306$) with the league's highest offensive efficiency (0.8786), while Türk Telekom presents the most balanced profile ($\Delta = 0.048$). No player from Çaydaş Bodrum or Tofaş reaches the efficient frontier across the three seasons, a pattern consistent with persistent rather than season-specific underperformance.

The panel of 16 multi-season players reveals that efficiency is neither a fixed trait nor random. Errick McCollum's three-season average of 0.9307 across three clubs suggests efficiency that is robust to team context. James Palmer Jr. (0.4921 ; 0.8312) and Kyle Allman Jr. (0.0584 ; 0.8619) trace the steepest upward trajectories, consistent with a league-specific learning curve. David Efiyani's mid-panel collapse (0.6981 ; 0.1602) following a transfer illustrates how roster change can impose a

severe but potentially temporary efficiency shock.

Several limitations suggest directions for future research. The equal-weighting assumption ($w = 0.5$) is a modelling convenience; preliminary sensitivity runs across $w_1 \in \{0.30, 0.40, 0.50, 0.60, 0.70\}$ produce team rankings stable to within two positions, though formal analysis would establish this more rigorously. FGA values reconstructed from season-average field goal percentages introduce near-perfect collinearity with FGM, rendering FGA slack uninterpretable in isolation. Position-stratified analysis would sharpen interpretation of the offensive-defensive asymmetry. Finally, extending the model to a dynamic NDEA specification in the spirit of Villa and Lozano (2018) would decompose panel efficiency changes into frontier-shift and catch-up components.

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Appendix Table 1.

Full Player-Season Dataset with Parallel Network SBM-DEA Efficiency Scores ($n = 300$)

Note: All statistics are per-game averages. Inputs: MPG (minutes per game), FGA (field goal attempts), FTA (free throw attempts). Offensive outputs: PPG (points), FGM (field goals made), FTM (free throws made), ORB (offensive rebounds). Defensive outputs: DRB (defensive rebounds), APG (assists), SPG (steals), BPG (blocks). Undesirable output: TOV (turnovers). $\theta_{Total} = 0.5 \cdot \theta_{Offensive} + 0.5 \cdot \theta_{Defensive}$. Green highlight (θ_{Total}) = fully efficient ($\theta \geq 0.9999$). Sorted by season then by θ_{Total} descending within each season.

				Input	Input	Input	Output-Off	Output-Off	Output-Off	Output-Off	Output-Def	Output-Def	Output-Def	Output-Def	Undesirable	Efficiency	Efficiency	Efficiency
Player	Team	Season	GP	MPG	FGA	FTA	PPG	FGM	FTM	ORB	DRB	APG	SPG	BPG	TOV	θ_{Total}	θ_{Off}	θ_{Def}
Season 2023–24 (n = 100)																		
Marcquise Reed	DEM	2023-24	30	29.7	14.9	5.7	21.1	7.2	5.0	0.9	3.2	3.7	2.00	0.10	2.3	1.0000	1.0000	1.0000
Daniel Oturu	MERK	2023-24	10	32.9	11.5	8.4	20.3	7.5	5.3	3.5	6.1	1.4	1.10	1.60	3.5	1.0000	1.0000	1.0000
Erick McCollum	PIN	2023-24	33	26.6	11.8	6.4	19.8	6.2	5.4	0.8	2.3	5.8	1.20	0.30	2.4	1.0000	1.0000	1.0000
Nathaniel Mason	MERK	2023-24	22	36.9	15.3	4.1	19.6	6.8	3.6	0.5	2.5	7.1	1.30	0.00	3.2	1.0000	1.0000	1.0000
Austin Wiley	TOF	2023-24	24	27.4	8.4	5.5	15.2	5.8	3.7	3.3	6.8	0.8	0.60	1.90	1.2	1.0000	1.0000	1.0000
Emanuel Terry	MANI	2023-24	32	28.7	8.1	3.5	12.8	5.0	2.8	2.6	5.9	1.4	1.10	0.70	1.4	1.0000	1.0000	1.0000
Marko Pecarski	MERK	2023-24	24	25.1	8.2	1.3	11.1	4.5	1.0	2.4	3.2	0.8	0.30	0.30	0.5	1.0000	1.0000	1.0000
Josh Carlton	DBI	2023-24	14	19.2	6.9	2.5	9.7	4.2	1.3	2.7	3.6	0.6	0.90	1.00	1.0	1.0000	1.0000	1.0000
Sertac Sanli	FEN	2023-24	37	18.1	5.8	1.7	9.1	3.5	1.2	1.1	3.0	1.1	0.40	0.60	0.8	1.0000	1.0000	1.0000
Mahir Agva	SOC	2023-24	32	17.4	6.2	2.7	9.0	3.4	2.2	1.8	2.8	1.2	0.60	0.30	0.8	1.0000	1.0000	1.0000
Enes Taskiran	DBI	2023-24	13	17.0	6.2	1.3	8.8	3.1	1.0	0.4	1.4	1.2	0.60	0.10	1.1	1.0000	1.0000	1.0000
Bugrahan Tuncer	GAL	2023-24	26	20.3	9.1	1.9	11.2	4.1	1.7	0.7	2.7	4.3	0.80	0.10	1.9	0.9636	0.9271	1.0000
Derek Willis	EFE	2023-24	25	25.4	6.4	1.5	10.4	3.7	1.4	1.2	3.5	1.2	1.00	0.50	0.9	0.9561	1.0000	0.9123
Yam Madar	FEN	2023-24	19	24.4	7.2	1.6	10.7	4.0	1.4	1.1	3.3	6.1	1.40	0.10	1.7	0.9442	0.8884	1.0000
Muhsin Yasar	DBI	2023-24	30	18.6	6.5	2.6	9.9	4.0	1.9	1.8	2.4	0.8	0.50	0.60	0.8	0.9430	1.0000	0.8860
Vernon Carey, Jr.	PIN	2023-24	23	23.6	8.8	3.3	13.6	5.7	2.1	1.7	4.5	1.5	0.60	0.80	1.2	0.8973	1.0000	0.7946
George Papagiannis	FEN	2023-24	21	22.3	7.1	1.1	9.9	4.2	0.9	1.9	3.8	1.1	0.60	1.00	1.2	0.8892	1.0000	0.7784
Evan Bruinsma	DEM	2023-24	29	27.4	9.0	1.8	11.3	4.5	1.2	1.5	3.4	1.4	1.00	0.20	0.7	0.8788	0.7575	1.0000
Yigitcan Saybir	TUR	2023-24	29	26.9	6.7	2.3	9.0	3.4	1.2	1.6	2.8	1.7	1.40	0.10	1.1	0.8627	0.7253	1.0000
Johnathan Motley	FEN	2023-24	19	20.1	9.3	3.5	14.5	5.9	2.5	1.7	3.3	1.7	0.40	0.60	1.9	0.8461	1.0000	0.6923
Erick Neal	BURS	2023-24	10	24.1	8.0	1.8	9.3	3.2	1.1	1.2	2.2	3.9	1.10	0.10	1.0	0.8302	0.6604	1.0000
Ahmet Duverioğlu	CAG	2023-24	27	24.8	8.0	3.4	12.3	5.0	2.3	1.9	4.4	2.3	0.90	0.90	1.8	0.8236	0.7999	0.8474
Kyle Allman, Jr.	BES	2023-24	21	22.0	7.4	4.5	10.0	2.7	3.9	0.3	1.9	3.1	0.60	0.30	1.3	0.8211	1.0000	0.6421
Elijah Bryant	EFE	2023-24	18	26.6	10.3	3.4	13.4	4.9	2.8	1.6	3.6	4.4	1.30	0.30	2.4	0.8187	0.8580	0.7795
Daniel Oturu	EFE	2023-24	21	25.7	9.2	4.9	15.0	6.0	3.1	2.9	2.9	1.5	0.50	1.10	1.7	0.8181	1.0000	0.6362
Nate Sestina	FEN	2023-24	18	23.9	7.7	0.8	9.6	3.6	0.6	1.6	3.5	1.1	0.70	0.30	0.9	0.8132	1.0000	0.6264
Jeremy Simmons	SOC	2023-24	32	25.7	6.8	2.7	10.3	4.3	1.6	1.9	3.3	1.1	0.90	0.70	1.0	0.8064	0.8931	0.7197
Darius Thompson	EFE	2023-24	25	27.7	9.6	2.1	12.7	4.8	1.5	0.8	1.8	4.5	1.10	0.50	1.2	0.8049	0.6098	1.0000
Johnny Hamilton	BURS	2023-24	25	26.2	7.4	3.1	10.8	4.4	2.0	1.9	5.0	1.0	0.50	1.60	1.4	0.8012	0.7908	0.8115
Rodrigue Beaubois	EFE	2023-24	27	25.6	10.1	2.6	14.4	4.9	2.4	0.5	2.2	3.1	1.00	0.20	1.2	0.7885	1.0000	0.5771
Michale Kyser	SAM	2023-24	12	32.9	9.6	1.4	10.9	4.9	1.0	1.8	5.2	1.8	0.70	1.40	1.6	0.7800	0.8543	0.7057
Tyrique Jones	EFE	2023-24	16	26.2	7.8	2.3	10.5	4.6	1.4	3.3	3.2	1.7	0.40	0.60	1.4	0.7651	1.0000	0.5302
Can Korkmaz	DBI	2023-24	24	19.8	7.3	3.7	9.7	2.6	2.9	0.4	1.7	3.5	0.50	0.00	0.7	0.7499	0.4998	1.0000
Shane Larkin	EFE	2023-24	15	33.1	10.9	4.1	16.8	5.3	3.5	0.3	2.8	6.7	0.90	0.10	1.9	0.7494	0.4988	1.0000
Klemen Prepelic	GAL	2023-24	20	25.9	9.0	5.2	14.2	3.7	4.5	0.5	2.4	5.6	0.40	0.10	2.2	0.7438	1.0000	0.4877
Marko Simonovic	BES	2023-24	12	21.5	7.3	2.8	11.3	4.4	2.3	1.8	3.1	1.3	0.60	0.20	1.3	0.7410	1.0000	0.4820
Cassius Winston	TOF	2023-24	28	29.2	9.9	4.3	14.6	4.5	4.0	0.5	2.4	5.3	0.80	0.10	2.2	0.7320	1.0000	0.4639
Steven Enoch	TUR	2023-24	30	24.5	7.4	3.0	11.4	4.3	2.5	1.5	3.5	0.9	0.40	0.60	1.6	0.7285	1.0000	0.4569
Nigel Hayes-Davis	FEN	2023-24	26	26.9	9.2	3.7	14.3	4.8	3.1	1.2	2.7	2.0	1.10	0.30	1.2	0.7224	0.8455	0.5994

Tarik Biberovic	FEN	2023-24	35	21.5	7.3	1.3	10.4	3.8	1.2	0.7	2.7	1.5	0.50	0.10	0.8	0.7197	1.0000	0.4393
Fatts Russell	MANI	2023-24	27	32.2	13.8	6.1	17.3	5.1	4.8	0.4	2.6	5.8	1.80	0.00	1.7	0.7127	0.4254	1.0000
Tyrone Wallace	TUR	2023-24	32	32.5	13.5	4.2	17.3	6.2	3.2	0.9	4.2	4.9	1.10	0.40	2.7	0.7118	0.6827	0.7410
Ryan Luther	MANI	2023-24	29	27.9	8.5	2.7	11.7	4.1	2.1	2.3	4.5	1.4	0.80	0.40	1.4	0.7101	0.8615	0.5588
David McCormack	GAL	2023-24	21	24.6	8.6	4.5	13.7	5.1	3.4	2.3	4.8	0.7	0.90	0.40	1.5	0.7036	0.8949	0.5123
David Efanayi	SOC	2023-24	30	31.7	13.6	6.8	19.8	6.0	5.7	0.8	2.0	4.0	0.80	0.20	2.6	0.6981	1.0000	0.3963
David McCormack	DBI	2023-24	10	25.3	8.3	4.3	13.7	5.3	3.1	4.2	5.6	0.2	0.80	0.40	1.5	0.6821	1.0000	0.3642
Philip Scrubb	BAHC	2023-24	26	28.3	7.0	2.4	10.5	3.2	2.2	0.4	1.5	4.2	0.80	0.10	1.4	0.6820	1.0000	0.3639
Bryant Crawford	SAM	2023-24	18	30.9	10.6	4.1	13.9	4.4	3.4	0.3	2.1	5.8	1.80	0.20	3.2	0.6708	0.3416	1.0000
Alexander Perez Kaufmann	DEM	2023-24	28	33.0	11.0	3.5	14.3	4.8	2.7	0.4	2.8	6.8	1.10	0.10	2.4	0.6699	0.3398	1.0000
Goktug Bas	SAM	2023-24	29	27.9	8.6	3.3	11.6	4.6	2.0	1.9	3.4	2.3	0.90	0.50	2.0	0.6665	0.7173	0.6157
Jerry Boutsiele	BAHC	2023-24	30	33.0	9.3	5.1	13.8	5.0	3.6	3.0	5.5	2.4	0.30	0.80	1.9	0.6589	0.8170	0.5007
Sadik Kabaca	GAL	2023-24	33	22.9	8.0	1.6	10.4	3.7	1.2	0.8	2.5	1.6	0.50	0.80	1.2	0.6560	0.6398	0.6721
Caleb Homesley	TOF	2023-24	25	29.3	13.0	3.2	16.4	5.7	2.6	0.6	3.6	3.8	1.00	0.40	2.0	0.6374	0.6347	0.6400
Melih Mahmutoglu	FEN	2023-24	39	19.8	6.8	1.2	9.0	3.2	0.9	0.1	1.1	1.3	0.40	0.00	0.4	0.6304	0.2608	1.0000
Axel Bouteille	BAHC	2023-24	30	30.5	12.5	1.9	16.1	6.2	1.5	1.3	3.2	2.4	0.70	0.10	1.3	0.6202	1.0000	0.2405
Anthony Brown	BURS	2023-24	30	33.2	12.5	3.1	16.6	6.0	2.6	0.9	4.5	2.8	1.10	0.20	2.0	0.6181	0.8125	0.4237
Dominic Artis	CAG	2023-24	29	27.8	10.5	2.9	12.1	3.9	2.4	0.7	2.3	3.2	1.70	0.10	1.9	0.6157	0.5770	0.6545
Tyler Cavanaugh	BAHC	2023-24	29	29.7	9.6	3.8	15.5	5.3	3.3	1.6	3.9	1.9	0.80	0.10	1.6	0.6151	1.0000	0.2302
Amar Alibegovic	CAG	2023-24	23	28.0	11.2	3.3	13.9	5.2	2.5	1.4	3.9	1.5	0.40	0.80	2.0	0.6126	0.7106	0.5146
Jordan Floyd	BURS	2023-24	21	26.6	12.5	4.9	17.0	5.7	4.2	0.3	1.9	3.2	1.40	0.40	2.4	0.6124	0.5100	0.7147
J.J. O'Brien	TOF	2023-24	27	30.3	9.9	4.2	13.7	5.0	3.0	1.1	2.6	3.3	1.60	0.10	1.6	0.5967	0.5257	0.6676
Rihards Lomazs	MERK	2023-24	12	34.7	10.5	6.3	14.7	4.1	5.0	0.8	2.0	2.3	0.50	0.10	2.6	0.5913	1.0000	0.1826
Kenan Sipahi	PIN	2023-24	35	27.7	6.6	2.1	9.0	3.2	1.5	0.8	2.9	5.2	0.90	0.10	1.7	0.5667	0.6256	0.5078
Vitto Brown	PIN	2023-24	36	30.2	9.8	2.3	13.4	4.7	1.9	0.6	4.0	1.4	0.50	0.60	1.1	0.5632	0.5826	0.5437
Yannick Franke	DEM	2023-24	10	30.7	12.9	4.5	17.6	5.7	3.4	0.9	4.0	2.5	1.20	0.10	1.3	0.5337	0.6886	0.3788
Mike Young	BURS	2023-24	29	29.8	9.6	3.6	13.1	4.9	2.5	1.3	4.5	3.1	0.40	0.30	1.9	0.5313	0.6029	0.4597
Nike Sibande	MERK	2023-24	12	26.0	10.3	3.3	14.7	5.4	2.4	0.7	3.3	1.5	0.60	0.30	2.1	0.5234	0.5750	0.4717
Kelan Martin	PIN	2023-24	35	31.6	9.1	2.3	13.4	4.9	1.8	0.5	4.0	1.9	0.80	0.20	1.0	0.5194	0.5947	0.4441
Nimrod Levi	SAM	2023-24	20	28.9	10.6	1.6	12.2	4.7	1.1	1.0	4.7	1.4	0.50	0.20	1.4	0.5122	0.6731	0.3513
Jalen Hudson	MERK	2023-24	10	25.9	11.0	4.3	14.7	5.1	2.9	0.7	2.7	1.7	0.80	0.40	1.6	0.5057	0.4566	0.5549
Sek Henry	SAM	2023-24	20	28.3	10.2	2.3	13.3	4.7	1.5	0.7	2.2	2.8	1.10	0.20	1.5	0.5053	0.5540	0.4567
Scottie Wilbekin	FEN	2023-24	20	23.1	8.8	2.1	13.6	4.3	1.8	0.2	1.7	4.1	0.70	0.00	1.1	0.8894	1.0000	0.7787
Markel Starks	SOC	2023-24	15	24.1	10.8	1.1	11.3	4.1	1.1	0.3	1.8	3.9	0.50	0.00	1.2	0.8195	1.0000	0.6390
Tyler Dorsey	FEN	2023-24	14	19.7	8.9	1.4	11.2	4.1	1.3	0.6	2.2	2.6	0.70	0.00	1.0	0.9474	1.0000	0.8947
James Palmer, Jr.	TUR	2023-24	31	27.6	10.5	3.9	15.0	5.3	2.2	0.5	2.4	3.1	1.10	0.30	1.4	0.4921	0.3966	0.5876
Muhammad-Ali Abdur-Rahkman	DBI	2023-24	28	28.1	10.3	2.5	11.1	3.8	1.9	0.6	1.7	3.7	1.20	0.10	1.2	0.4911	0.4398	0.5424
Jaron Johnson	CAG	2023-24	30	28.8	9.1	3.1	12.2	4.0	2.4	0.8	3.1	1.4	0.50	0.20	1.0	0.4621	0.5428	0.3814
James Anderson	MANI	2023-24	26	29.3	8.0	1.9	10.5	3.7	1.4	0.7	2.8	2.1	0.60	0.20	1.7	0.4385	0.5260	0.3510
Will Clyburn	EFE	2023-24	19	27.9	9.9	2.3	10.8	4.1	1.7	0.9	4.2	3.2	1.00	0.10	1.8	0.4327	0.5519	0.3134
Tony Taylor	BAHC	2023-24	24	29.0	10.1	1.8	13.0	4.9	1.5	0.3	1.3	5.3	1.00	0.10	1.8	0.4325	0.4382	0.4269
Ridvan Oncel	DBI	2023-24	11	23.6	7.7	3.4	9.0	2.9	2.4	0.5	2.9	2.7	0.70	0.20	2.5	0.4310	0.3678	0.4942
Khyri Thomas	SOC	2023-24	22	30.8	11.5	3.7	14.0	5.0	2.6	0.8	3.4	3.3	1.40	0.10	2.0	0.4272	0.4640	0.3904
Derek Needham	BES	2023-24	32	25.7	9.7	2.4	13.2	4.3	2.1	0.3	1.2	4.4	1.10	0.10	2.8	0.4245	0.4952	0.3537
Matt Mitchell	BES	2023-24	34	26.0	7.4	3.4	9.9	3.6	2.1	1.1	2.7	2.0	0.60	0.10	1.4	0.4198	0.5849	0.2548
David Michineau	BURS	2023-24	27	29.7	10.5	2.3	11.7	4.8	1.5	0.7	2.0	3.8	1.00	0.10	1.3	0.4150	0.4760	0.3540
Jonah Mathews	BES	2023-24	34	27.7	11.9	2.9	14.8	5.4	2.3	0.4	1.8	2.7	1.30	0.10	2.3	0.3920	0.4440	0.3401
Matt Mooney	SAM	2023-24	17	27.4	10.5	1.6	11.8	4.4	1.4	0.8	1.8	3.2	1.80	0.00	2.5	0.8813	0.7626	1.0000
Pako Cruz	MANI	2023-24	32	32.5	12.5	2.9	16.8	5.9	2.4	0.6	2.5	4.4	0.90	0.00	2.9	0.6231	0.7171	0.5291
Darrun Hilliard	PIN	2023-24	14	26.1	8.6	2.8	12.3	3.7	2.6	0.3	2.6	3.8	0.60	0.00	1.9	0.6400	0.6877	0.5923

James Woodard	DBI	2023-24	16	25.4	9.4	1.5	12.4	4.4	1.2	0.6	2.4	2.4	0.80	0.00	1.8	0.6131	0.6547	0.5716
Kristers Zoriks	SOC	2023-24	27	26.0	8.3	3.0	10.1	3.1	2.3	0.3	1.8	3.4	0.60	0.10	1.4	0.2984	0.2876	0.3093
Roko Badzim	MERK	2023-24	10	28.0	9.2	1.9	11.4	3.9	1.5	0.7	2.3	2.3	1.10	0.00	1.6	0.5601	0.5594	0.5608
Omar Prewitt	TOF	2023-24	11	25.3	8.6	1.9	10.6	3.5	1.4	0.7	3.2	2.2	0.50	0.00	1.3	0.5580	0.5323	0.5836
Janis Timma	DBI	2023-24	10	26.4	8.1	1.6	11.4	3.6	1.3	0.5	4.1	1.2	1.10	0.00	1.1	0.6944	0.5205	0.8683
Dee Bost	GAL	2023-24	24	29.3	11.3	3.0	12.9	4.2	2.3	0.8	4.0	5.5	1.40	0.00	1.7	0.7552	0.5104	1.0000
Chris Warren	CAG	2023-24	30	26.6	10.7	2.0	13.0	4.5	1.7	0.3	1.7	3.5	0.80	0.00	1.9	0.5005	0.4398	0.5611
Brendan Adams	DBI	2023-24	17	28.1	9.8	2.3	10.1	3.9	1.5	0.5	1.9	5.1	0.70	0.00	1.8	0.4778	0.3761	0.5794
Jaylon Brown	PIN	2023-24	25	23.5	7.0	2.9	10.2	3.1	2.4	0.2	1.7	2.6	0.70	0.00	1.4	0.4576	0.3074	0.6078
Kendrick Ray	DEM	2023-24	19	22.2	9.6	1.9	10.7	4.2	1.4	0.2	2.1	2.3	0.50	0.00	1.9	0.4108	0.2527	0.5690
Kyle Allman, Jr.	DBI	2023-24	10	30.3	12.7	4.2	12.4	3.9	3.4	0.1	3.4	5.1	0.50	0.00	3.0	0.3126	0.1169	0.5083
Season 2024–25 (n = 100)																		
Jo Acuil	MANI	2024-25	21	26.4	11.1	6.6	17.2	6.6	3.9	2.6	4.4	1.0	0.80	1.00	1.8	1.0000	1.0000	1.0000
Erick McCollum	PIN	2024-25	12	27.2	10.4	4.5	16.0	4.8	4.4	1.0	1.2	5.2	0.80	0.50	1.7	1.0000	1.0000	1.0000
James Webb III	PIN	2024-25	12	30.1	10.8	2.4	15.3	5.3	1.9	1.8	4.9	1.5	2.00	0.40	1.0	1.0000	1.0000	1.0000
Braian Angola-Rodas	TUR	2024-25	24	24.6	8.8	4.6	13.4	3.7	4.2	0.7	4.0	4.8	0.90	0.10	1.7	1.0000	1.0000	1.0000
Gabriel Olaseni	MER	2024-25	32	26.7	8.2	4.2	12.7	4.7	3.3	3.0	5.4	1.3	0.60	0.50	2.0	1.0000	1.0000	1.0000
Martin Krampelj	YAL	2024-25	29	23.3	7.4	3.2	12.4	4.3	2.9	1.3	3.7	1.0	1.40	0.40	1.0	1.0000	1.0000	1.0000
Martynas Sajus	DEM	2024-25	32	24.8	6.0	4.9	12.1	4.1	3.9	2.5	3.2	1.4	0.80	1.30	1.6	1.0000	1.0000	1.0000
Jaime Echenique	SOC	2024-25	29	17.2	7.1	4.8	11.3	3.9	3.6	2.6	2.4	0.8	0.40	0.70	1.2	1.0000	1.0000	1.0000
Rodrigue Beaubois	EFE	2024-25	13	18.6	8.0	0.9	11.2	4.1	0.8	0.1	1.9	2.1	0.70	0.80	0.7	1.0000	1.0000	1.0000
Ebuka Izundu	GAL	2024-25	30	19.0	6.1	3.0	10.7	4.2	2.2	3.0	3.4	0.6	0.80	0.70	0.9	1.0000	1.0000	1.0000
Melih Mahmutoglu	FEN	2024-25	39	19.6	6.8	0.6	9.6	3.4	0.5	0.2	1.0	0.7	0.20	0.00	0.4	1.0000	1.0000	1.0000
Kris Bankston	TOF	2024-25	33	21.1	4.7	2.5	9.2	3.9	1.4	2.0	3.0	1.0	0.90	0.80	0.8	1.0000	1.0000	1.0000
Javon Freeman-Liberty	MANI	2024-25	1	28.7	9.0	0.0	9.0	4.0	0.0	0.0	5.0	2.0	1.00	0.00	0.0	1.0000	1.0000	1.0000
Arturs Zagars	FEN	2024-25	22	17.6	5.3	3.0	8.4	2.4	2.5	0.4	0.9	2.9	0.90	0.00	1.7	1.0000	1.0000	1.0000
Egemen Guven	MERK	2024-25	14	19.1	6.4	0.9	8.4	3.9	0.6	0.9	3.1	1.5	0.30	0.60	0.7	1.0000	1.0000	1.0000
Sertac Sanli	FEN	2024-25	29	17.6	5.3	2.1	8.3	2.8	1.8	1.4	2.9	1.0	0.20	0.40	0.6	1.0000	1.0000	1.0000
Berk Ugurlu	BES	2024-25	41	23.5	5.7	0.7	8.3	3.3	0.6	0.6	1.5	3.4	0.70	0.00	0.5	1.0000	1.0000	1.0000
Marko Simonovic	BAHC	2024-25	34	17.3	5.6	1.5	8.3	3.1	1.2	1.6	3.0	1.0	0.60	0.30	0.9	1.0000	1.0000	1.0000
Bonzie Colson, Jr.	FEN	2024-25	25	18.7	6.1	1.2	8.3	3.2	0.9	1.0	2.9	1.0	0.80	0.20	0.6	0.9450	0.8900	1.0000
Daniel Oturu	EFE	2024-25	31	22.1	8.5	4.7	14.5	5.9	2.7	2.5	2.9	1.5	0.60	0.90	1.1	0.9326	1.0000	0.8651
Donte Grantham	BURS	2024-25	31	29.7	8.9	2.7	12.4	4.7	2.1	2.3	5.5	2.3	0.70	0.20	1.5	0.9260	0.8520	1.0000
Kyle Alexander	TUR	2024-25	34	26.6	6.9	3.4	11.1	4.3	2.3	2.6	4.1	1.0	0.50	1.10	0.8	0.9151	0.8303	1.0000
Axel Bouteille	BAHC	2024-25	36	21.1	7.5	1.0	8.7	3.3	0.8	0.8	2.4	1.5	0.40	0.10	0.3	0.9127	0.8255	1.0000
Omari Moore	DBI	2024-25	30	34.1	12.9	3.0	15.7	6.1	2.0	1.1	4.2	5.5	1.30	0.60	3.5	0.9118	0.8236	1.0000
Sharife Cooper	MERK	2024-25	6	30.2	14.2	4.7	15.8	5.5	3.8	1.3	3.0	6.0	1.50	0.00	4.5	0.8965	0.7929	1.0000
Evan Bruinsma	DEM	2024-25	25	22.7	6.8	1.9	9.3	3.5	1.3	1.4	4.6	1.3	0.60	0.10	1.2	0.8914	0.7828	1.0000
Martynas Echodas	MANI	2024-25	9	26.3	8.9	4.7	13.7	5.0	3.7	2.7	4.8	1.0	0.90	0.40	2.0	0.8830	1.0000	0.7660
Luka Brajkovic	DBI	2024-25	22	20.4	5.9	2.0	8.8	3.9	1.1	2.5	2.8	1.2	0.50	0.70	1.2	0.8813	1.0000	0.7626
Chris Chiozza	MANI	2024-25	26	24.0	7.0	1.1	8.5	2.9	1.0	0.3	2.3	5.9	1.10	0.00	2.0	0.8547	0.7093	1.0000
Rolands Smits	EFE	2024-25	18	17.6	6.2	1.6	8.6	3.2	1.3	1.0	2.3	1.4	0.50	0.20	0.9	0.8438	0.8577	0.8298
Yoan Makoundou	TUR	2024-25	32	18.4	6.7	2.6	8.3	3.1	1.8	1.2	2.8	0.7	0.60	0.80	1.4	0.8416	0.6832	1.0000
Muhsin Yasar	PIN	2024-25	29	22.9	8.8	3.0	14.2	5.9	2.5	1.9	3.1	1.3	0.50	0.70	1.7	0.8408	1.0000	0.6817
Markel Starks	DEM	2024-25	28	28.3	10.5	3.1	14.3	4.5	2.9	0.5	2.0	5.7	1.00	0.00	1.5	0.8375	0.6750	1.0000
Brodrick Thomas	MANI	2024-25	23	27.2	6.3	2.4	8.9	3.0	1.7	1.2	4.0	2.0	1.20	0.90	1.4	0.8098	0.6392	0.9803
Jaleen Smith	BAHC	2024-25	35	25.1	7.7	1.9	9.8	3.4	1.5	0.7	2.1	4.7	1.20	0.00	1.3	0.7990	0.5980	1.0000
Jerry Boutsiele	PIN	2024-25	10	22.3	6.0	4.6	11.2	4.0	3.2	2.9	2.7	1.1	0.30	0.70	0.8	0.7943	1.0000	0.5886
Dustin Sleva	BES	2024-25	42	25.3	7.4	2.2	11.0	4.0	1.7	2.4	3.5	1.6	1.10	0.20	1.1	0.7940	1.0000	0.5880
Fabian White	MANI	2024-25	30	26.0	11.5	2.2	14.5	5.9	1.5	1.8	2.9	1.1	0.60	0.70	1.4	0.7931	1.0000	0.5862

Bugrahan Tuncer	GAL	2024-25	30	21.1	7.8	2.6	9.3	2.9	2.3	0.5	2.3	4.4	0.70	0.00	1.7	0.7895	0.5791	1.0000
Tyler Cook	MERK	2024-25	24	27.9	9.2	6.0	15.0	5.8	3.4	2.3	4.5	1.5	0.60	0.50	2.1	0.7815	0.8943	0.6687
Stefan Moody	MERK	2024-25	20	29.7	9.5	2.8	12.5	3.9	2.5	0.5	1.9	5.8	1.10	0.40	2.4	0.7766	0.5532	1.0000
Jordan Nwora	EFE	2024-25	29	22.5	9.9	2.4	14.9	5.3	1.9	0.8	2.9	1.5	0.90	0.20	1.6	0.7738	1.0000	0.5476
Tres Tinkle	DBI	2024-25	30	31.5	11.3	3.5	15.4	5.4	2.7	2.2	4.3	1.8	1.30	0.20	1.7	0.7546	1.0000	0.5092
Wesley Van Beck	SOC	2024-25	29	26.2	8.7	4.4	14.8	4.3	3.9	0.7	1.9	3.9	1.30	0.10	2.2	0.7477	1.0000	0.4953
Jonah Mathews	BES	2024-25	41	26.5	13.6	1.7	15.7	6.2	1.1	0.6	1.8	2.7	0.90	0.20	1.7	0.7351	1.0000	0.4701
Fatts Russell	PIN	2024-25	14	26.0	12.9	4.5	16.1	5.3	3.6	0.3	2.3	4.7	1.60	0.10	1.6	0.7212	0.4424	1.0000
Nigel Hayes-Davis	FEN	2024-25	36	25.2	9.6	3.4	13.1	4.4	2.9	1.3	3.1	2.0	0.90	0.30	1.0	0.7188	0.7757	0.6619
Vrenz Bleijenbergh	MERK	2024-25	29	30.2	8.2	3.0	11.6	3.7	2.3	0.6	4.4	4.0	1.10	1.00	1.8	0.7171	0.4343	1.0000
Hans Vanwijjn	MERK	2024-25	22	25.1	7.8	2.4	10.6	4.0	1.9	1.9	2.6	2.1	0.70	0.30	1.0	0.7169	0.8420	0.5917
Tai Odiase	BAHC	2024-25	36	22.0	6.5	2.0	9.6	4.1	1.4	1.8	2.2	0.6	0.30	0.90	0.9	0.7149	0.9113	0.5186
Tarik Biberovic	FEN	2024-25	29	20.8	7.5	1.4	9.7	3.2	1.3	0.4	3.0	1.7	0.50	0.10	1.4	0.6928	1.0000	0.3856
James Palmer, Jr.	GAL	2024-25	33	31.7	12.2	3.3	16.3	5.9	1.7	0.5	3.0	3.9	1.40	0.40	2.1	0.6892	0.6205	0.7579
Jaylen Johnson	YAL	2024-25	24	25.7	9.8	2.6	11.7	4.7	1.5	2.0	3.6	2.0	0.50	0.40	1.9	0.6873	0.7533	0.6212
Bryson Williams	SOC	2024-25	26	18.9	7.2	2.4	8.5	3.2	1.4	1.3	2.6	0.8	0.60	0.40	1.2	0.6814	0.6781	0.6847
Alexander Perez Kaufmann	TOF	2024-25	29	30.7	10.9	3.1	14.7	4.8	2.8	0.2	2.7	6.3	1.00	0.00	2.1	0.6779	0.3557	1.0000
Egehan Arna	MERK	2024-25	15	28.7	10.9	2.1	14.3	5.1	1.6	1.9	3.6	3.1	0.70	0.10	1.3	0.6712	1.0000	0.3424
Kenan Sipahi	PIN	2024-25	13	28.1	6.5	2.1	9.5	3.2	1.8	0.3	2.7	5.6	0.80	0.10	1.8	0.6525	0.4227	0.8824
Yigitcan Saybir	TOF	2024-25	33	25.6	8.2	2.5	11.2	4.5	1.5	1.4	3.7	1.6	1.10	0.20	1.2	0.6455	0.7083	0.5828
Jermaine Love-Roberts	DEM	2024-25	31	29.4	11.7	5.0	16.9	5.6	4.4	0.4	2.4	3.6	1.40	0.20	3.1	0.6284	0.6771	0.5797
Kyle Allman, Jr.	BES	2024-25	42	21.2	7.3	4.8	9.6	2.7	3.7	0.2	1.9	4.5	0.60	0.10	2.0	0.6161	0.2322	1.0000
Shane Larkin	EFE	2024-25	19	25.6	8.2	3.9	12.6	3.7	3.1	0.2	2.6	5.2	1.30	0.20	1.9	0.6137	0.2275	1.0000
Isaiah Pineiro	MER	2024-25	31	26.0	7.4	2.9	9.4	3.1	2.4	1.3	3.5	1.6	0.90	0.20	1.4	0.6036	0.7016	0.5056
David Michineau	BURS	2024-25	31	28.4	12.3	2.5	14.2	6.0	1.6	1.3	2.1	3.3	1.10	0.10	1.5	0.5891	0.8289	0.3493
Tyler Cavanaugh	BAHC	2024-25	36	26.3	6.6	3.4	10.3	3.2	2.8	1.6	4.1	1.4	0.70	0.10	1.5	0.5691	0.7968	0.3415
Ben McLemore	MERK	2024-25	29	25.1	9.0	1.8	12.3	4.1	1.4	0.6	2.6	1.8	1.00	0.20	1.9	0.5667	0.6225	0.5109
Both Gach	DBI	2024-25	28	25.6	8.9	1.8	11.1	4.1	1.5	0.7	1.8	2.1	0.60	0.20	1.6	0.5436	0.6737	0.4135
Kelan Martin	BES	2024-25	14	19.7	7.6	1.1	9.8	3.6	0.9	0.3	1.7	0.5	0.60	0.40	0.8	0.5396	0.5959	0.4834
Sehmus Hazer	BAHC	2024-25	33	22.3	8.2	4.2	10.7	3.4	3.0	0.5	2.0	2.6	1.10	0.20	1.4	0.5258	0.3925	0.6591
Anthony Brown	TUR	2024-25	35	30.5	10.9	3.0	14.7	5.1	2.6	0.4	3.4	3.2	0.70	0.30	2.2	0.5216	0.5070	0.5362
Furkan Korkmaz	BAHC	2024-25	21	21.3	9.3	3.6	12.5	3.8	3.1	0.4	1.6	2.0	1.10	0.10	1.1	0.5170	0.5252	0.5089
Travis McConico	YAL	2024-25	27	23.5	7.0	2.3	8.9	2.9	1.8	0.9	3.0	2.4	1.00	0.10	1.7	0.5067	0.6160	0.3973
Saben Lee	MANI	2024-25	12	31.5	10.5	9.2	18.7	5.3	7.1	0.8	2.9	6.0	1.00	0.00	3.0	0.9281	1.0000	0.8561
Marcquise Reed	TOF	2024-25	31	28.5	13.0	4.8	17.8	6.4	4.2	0.9	3.3	3.9	1.60	0.00	2.2	0.9447	1.0000	0.8895
Yannick Franke	DEM	2024-25	31	29.8	11.5	5.2	17.6	5.0	4.6	0.5	4.6	2.4	0.30	0.00	1.9	0.7110	1.0000	0.4219
Otis Livingston II	GAL	2024-25	18	29.0	12.2	1.8	15.2	5.6	1.7	0.4	1.7	4.4	0.50	0.00	2.1	0.7586	1.0000	0.5172
Damien Jefferson	PIN	2024-25	12	24.9	7.9	0.5	10.0	3.8	0.3	1.7	2.3	2.1	0.80	0.00	1.5	0.8309	1.0000	0.6618
Marko Guduric	FEN	2024-25	36	20.1	5.6	3.2	9.5	2.9	2.7	0.4	2.1	3.6	0.70	0.00	2.0	0.9518	1.0000	0.9036
J.J. O'Brien	TOF	2024-25	25	25.1	7.6	3.0	10.2	3.7	2.3	1.0	2.1	2.1	1.10	0.10	1.3	0.4802	0.5914	0.3690
Hugo Besson	MANI	2024-25	29	27.8	11.3	4.7	16.6	5.3	3.8	0.5	3.0	2.9	0.60	0.10	2.0	0.4784	0.6494	0.3075
Breein Tyree	SOC	2024-25	29	28.5	12.8	2.6	13.9	5.1	2.0	0.4	2.8	3.8	0.90	0.20	2.6	0.4701	0.4244	0.5159
Wade Baldwin IV	FEN	2024-25	27	21.0	8.9	3.2	11.1	4.0	2.3	0.3	2.3	3.8	0.60	0.10	1.9	0.4487	0.2721	0.6254
Grant Sheffield	YAL	2024-25	27	28.7	12.5	2.8	15.3	5.6	2.0	0.4	2.3	4.2	0.60	0.10	2.4	0.4256	0.4980	0.3531
Elijah Bryant	EFE	2024-25	28	21.8	8.0	2.3	10.5	3.9	1.9	0.2	2.0	3.0	1.10	0.10	1.4	0.4169	0.2983	0.5355
Pako Cruz	MER	2024-25	32	30.5	12.4	2.2	15.6	5.5	1.8	0.5	2.7	4.6	1.10	0.00	1.9	0.7701	0.8079	0.7323
Uros Trifunovic	TOF	2024-25	32	24.0	8.3	2.5	11.3	3.9	1.7	0.5	1.8	1.4	0.50	0.10	0.7	0.3689	0.4387	0.2991
Yunus Sonsirma	MANI	2024-25	30	27.8	6.2	1.1	8.8	3.0	0.9	0.6	2.0	3.1	0.50	0.00	1.5	0.6257	0.7153	0.5362
Tyree Appleby	DBI	2024-25	29	25.0	10.1	4.3	12.7	3.4	3.7	0.2	1.4	4.2	0.80	0.10	2.2	0.3516	0.2704	0.4329
David DeJulius	BURS	2024-25	13	29.9	11.0	1.8	13.1	5.1	1.3	0.8	1.3	5.8	0.60	0.00	1.8	0.6629	0.6982	0.6275

Derek Needham	BES	2024-25	40	25.0	9.9	2.2	12.7	4.3	1.7	0.7	1.6	3.4	1.10	0.00	1.5	0.6641	0.6246	0.7036
Jaylon Brown	BURS	2024-25	31	29.2	10.5	4.0	15.5	5.1	3.0	0.5	2.3	3.3	1.50	0.00	2.8	0.6215	0.5397	0.7032
Justin Cobbs	MER	2024-25	32	32.0	9.9	5.2	14.7	4.4	4.7	0.3	2.2	5.8	0.80	0.00	1.8	0.6374	0.5346	0.7402
Kenan Sipahi	BAHC	2024-25	19	22.0	6.4	2.3	9.1	2.9	1.9	0.4	1.8	4.8	0.70	0.00	1.6	0.7381	0.4761	1.0000
David Mutaf	BURS	2024-25	30	25.8	10.0	2.5	12.0	4.2	2.0	0.5	2.4	1.7	0.90	0.00	1.4	0.5474	0.4713	0.6234
David Nichols	YAL	2024-25	18	30.0	8.9	2.0	12.4	4.4	1.3	0.4	1.2	5.1	1.00	0.00	2.7	0.4854	0.4428	0.5281
Will Cummings	GAL	2024-25	30	24.2	9.8	3.0	12.5	4.5	2.4	0.4	1.6	3.4	1.00	0.00	2.0	0.5399	0.3962	0.6836
Olivier Hanlan	TUR	2024-25	33	22.3	7.5	2.5	9.8	3.3	2.1	0.3	2.1	4.0	0.30	0.00	1.5	0.4905	0.3916	0.5893
Dewayne Russell	SOC	2024-25	29	25.7	8.0	1.9	8.6	3.0	1.7	0.2	1.3	5.4	0.80	0.00	1.9	0.5111	0.3529	0.6693
Damyean Dotson	SOC	2024-25	23	24.4	7.0	1.5	10.0	3.4	1.2	0.2	2.6	1.7	0.50	0.00	0.7	0.4970	0.3289	0.6651
David Efanayi	MER	2024-25	19	24.5	9.7	1.9	12.8	4.7	1.4	0.2	0.7	2.2	0.60	0.00	1.6	0.3548	0.3205	0.3891
Rihards Lomazs	MERK	2024-25	10	31.3	10.4	3.6	12.7	4.1	2.8	0.3	2.5	3.1	1.30	0.00	1.3	0.4910	0.2759	0.7062
Season 2025–26 (n = 100)																		
Brandon Childress	BURS	2025-26	30	29.9	10.7	5.0	14.9	4.3	4.5	0.2	2.4	6.8	1.80	0.00	3.3	1.0000	1.0000	1.0000
Anthony Cowan	MER	2025-26	29	26.7	9.2	6.8	14.9	3.7	5.3	0.2	1.4	6.8	0.80	0.10	2.8	1.0000	1.0000	1.0000
Talen Horton-Tucker	FEN	2025-26	31	21.1	9.5	4.5	13.2	4.4	3.4	1.0	2.5	3.0	1.10	0.60	1.9	1.0000	1.0000	1.0000
Maozinha Pereira	MANI	2025-26	26	24.4	9.0	1.8	11.7	5.0	1.1	2.2	3.8	1.2	1.40	1.60	0.9	1.0000	1.0000	1.0000
Christian Bishop	PIN	2025-26	17	19.3	6.1	4.5	10.6	3.8	3.1	1.4	3.3	0.9	1.20	0.10	1.2	1.0000	1.0000	1.0000
Trevion Williams	BAHC	2025-26	34	23.0	8.3	1.8	10.4	4.6	1.1	3.1	6.0	2.5	0.50	0.30	1.7	1.0000	1.0000	1.0000
Ronald March, Jr.	MER	2025-26	30	18.2	7.6	1.2	9.5	3.6	0.8	0.7	2.5	1.3	1.50	0.40	1.2	1.0000	1.0000	1.0000
Brice Dessert	EFE	2025-26	26	19.1	4.3	2.7	8.5	3.5	1.4	1.2	2.0	0.5	0.30	1.30	0.9	1.0000	1.0000	1.0000
B.J. Boston, Jr.	FEN	2025-26	19	17.3	6.8	2.1	8.4	2.9	1.7	1.0	1.7	0.7	0.40	0.10	0.7	1.0000	1.0000	1.0000
Ismael Kamagate	BES	2025-26	20	17.6	5.3	2.6	8.4	3.2	2.1	2.8	3.1	0.4	0.60	1.10	0.7	1.0000	1.0000	1.0000
Martynas Sajus	SOC	2025-26	30	20.2	5.3	3.2	9.5	3.6	2.3	2.4	2.4	1.4	0.90	0.90	1.9	0.9137	1.0000	0.8273
Kris Bankston	TUR	2025-26	29	20.4	4.6	2.1	8.0	3.2	1.5	2.0	2.6	1.2	0.60	0.90	0.9	0.9074	1.0000	0.8148
Vincent Poirier	EFE	2025-26	12	22.5	6.3	2.9	10.6	4.0	2.5	2.4	3.8	1.6	1.10	0.50	1.1	0.8978	1.0000	0.7957
Vrenz Bleijenbergh	MERK	2025-26	19	34.5	10.0	4.7	14.3	4.0	4.1	0.8	5.1	4.3	1.70	0.70	2.7	0.8819	0.7638	1.0000
Anthony Brown	BES	2025-26	39	24.8	7.8	1.6	10.1	3.4	1.4	0.7	3.7	2.5	0.60	0.20	1.0	0.8748	0.7497	1.0000
Petr Cornelie	ENEN	2025-26	32	24.0	8.1	3.1	10.6	3.9	1.8	2.0	4.2	1.5	0.90	0.60	1.0	0.8743	0.7485	1.0000
Kyle Alexander	TUR	2025-26	26	24.0	6.1	2.4	9.8	3.8	2.0	2.5	3.5	1.1	0.70	1.10	1.0	0.8691	1.0000	0.7382
Kyle Allman, Jr.	TUR	2025-26	22	21.5	8.8	6.3	12.0	3.4	4.3	0.1	2.2	3.3	0.70	0.30	2.3	0.8619	1.0000	0.7238
Gabriel Olaseni	MER	2025-26	30	25.9	7.0	3.9	11.1	4.0	3.0	2.7	5.1	1.7	0.70	0.40	2.0	0.8350	1.0000	0.6701
James Palmer, Jr.	GAL	2025-26	32	29.8	13.3	2.8	16.2	6.5	1.3	0.7	3.4	4.6	1.30	0.10	1.8	0.8312	1.0000	0.6623
Sehmus Hazer	EFE	2025-26	36	19.2	7.3	3.8	10.8	3.5	2.7	0.4	1.6	2.1	0.80	0.20	1.1	0.8086	1.0000	0.6172
Keye Van Der Vuurst De Vries	DEM	2025-26	29	31.9	9.4	4.1	12.4	3.5	3.7	0.4	2.9	8.7	1.00	0.00	3.6	0.8016	0.6033	1.0000
Jayce Johnson	MANI	2025-26	30	21.6	6.1	4.3	9.1	3.3	2.6	3.8	3.7	0.8	0.40	0.60	1.2	0.7945	1.0000	0.5889
Errick McCollum	GAL	2025-26	28	22.2	11.2	4.2	14.8	4.9	3.5	0.9	2.2	2.0	0.80	0.30	1.2	0.7922	1.0000	0.5843
Saben Lee	EFE	2025-26	10	22.9	7.1	5.3	11.6	3.4	4.1	0.7	1.7	4.4	0.70	0.10	1.8	0.7887	1.0000	0.5773
Devon Dotson	BES	2025-26	39	20.3	7.9	3.2	11.0	3.7	2.5	0.7	2.0	4.4	0.80	0.00	1.3	0.7857	0.5714	1.0000
Wade Baldwin IV	FEN	2025-26	30	21.8	8.4	4.3	12.6	4.1	3.4	0.5	2.4	4.8	0.80	0.20	2.2	0.7782	0.5564	1.0000
Ante Zizic	BES	2025-26	29	22.1	6.2	4.2	11.4	4.1	3.2	2.4	3.9	1.0	0.30	0.70	1.3	0.7758	1.0000	0.5517
Egehan Arna	ENEN	2025-26	32	29.5	8.2	2.1	10.7	3.7	1.5	0.8	4.3	2.1	1.30	0.20	1.1	0.7732	0.5464	1.0000
Angel Delgado	TRA	2025-26	25	21.3	7.2	2.2	9.7	4.2	1.3	2.1	3.5	1.0	0.80	0.40	1.2	0.7652	0.8888	0.6416
Fabian White	GAL	2025-26	32	26.2	8.9	1.9	10.6	4.2	1.2	2.3	3.3	1.4	0.80	0.80	1.1	0.7600	0.8484	0.6717
Marquise Reed	TRA	2025-26	32	30.9	15.0	6.8	23.3	8.1	5.9	0.8	2.9	5.0	1.90	0.10	2.8	0.7593	1.0000	0.5185
Dogus Ozdemiroglu	TUR	2025-26	32	26.0	9.1	4.4	11.3	3.5	2.8	0.9	2.9	5.2	2.20	0.20	2.6	0.7586	0.5172	1.0000
Jeremy Simmons	ENEN	2025-26	32	24.7	5.4	2.0	8.5	3.7	1.1	2.1	2.5	1.5	0.90	0.20	0.8	0.7408	1.0000	0.4816
Justin Alston	PIN	2025-26	30	19.4	6.3	1.0	7.7	3.0	0.8	1.0	2.5	1.0	0.50	0.20	1.0	0.7375	1.0000	0.4751
Alexander Perez Kaufmann	TOF	2025-26	30	29.0	8.9	2.9	12.6	4.3	2.3	0.5	2.1	6.4	1.20	0.20	1.9	0.7359	0.4718	1.0000
Mike Smith	BURS	2025-26	10	30.6	10.8	4.1	15.0	4.9	3.5	0.4	1.6	6.6	0.90	0.00	2.0	0.7298	0.4596	1.0000

Erxhan Osmani	EFE	2025-26	34	21.4	7.4	2.6	9.9	3.5	2.3	1.3	3.4	1.8	0.70	0.30	1.8	0.7266	0.8392	0.6141
Isaiah Miles	MERK	2025-26	20	26.5	7.1	2.1	11.3	3.9	1.8	0.9	3.2	1.1	0.90	0.30	0.9	0.7264	1.0000	0.4528
Marek Blazevic	TOF	2025-26	28	26.1	9.0	3.9	15.0	6.1	2.7	2.5	4.4	1.8	0.90	0.20	1.9	0.7206	1.0000	0.4412
Landry Nnoko	BURS	2025-26	30	25.6	6.0	2.8	8.6	3.3	2.0	2.9	4.1	0.9	0.60	0.60	1.2	0.7165	0.8589	0.5741
Conor Morgan	BES	2025-26	35	21.8	6.5	1.8	9.0	3.2	1.5	1.0	3.3	1.7	0.40	0.50	1.1	0.7092	0.8037	0.6147
Langston Galloway	ENEN	2025-26	32	19.8	7.1	2.4	9.0	2.7	2.0	0.4	2.1	1.2	1.00	0.10	0.5	0.7026	0.4051	1.0000
Erik Stevenson	MANI	2025-26	18	24.8	12.2	1.1	11.7	4.2	0.9	0.8	2.8	2.4	0.70	0.40	2.1	0.6955	0.8255	0.5655
Tony Taylor	TRA	2025-26	28	25.2	8.3	2.2	11.1	3.9	1.9	0.3	1.5	4.6	0.60	0.10	1.1	0.6941	0.3883	1.0000
Tyler Cavanaugh	BAHC	2025-26	32	27.1	8.0	2.8	11.7	3.9	2.7	1.9	3.6	1.7	0.90	0.20	1.0	0.6929	1.0000	0.3859
Jack White	MER	2025-26	30	27.7	7.0	1.7	10.0	3.8	0.9	1.5	3.7	1.3	0.80	0.60	1.0	0.6907	0.7902	0.5912
Samet Geyik	PIN	2025-26	27	25.7	6.5	1.9	8.1	3.2	1.2	2.0	3.4	1.0	0.90	0.50	1.3	0.6857	0.8050	0.5664
Jerome Robinson	GAL	2025-26	24	20.5	6.0	2.0	9.0	3.0	1.8	0.5	1.8	1.8	0.80	0.10	1.0	0.6744	1.0000	0.3489
Artur Konontsuk	BURS	2025-26	30	23.3	6.6	0.9	8.4	3.0	0.8	0.6	2.5	0.8	0.40	0.20	0.9	0.6710	1.0000	0.3420
Mahir Agva	MERK	2025-26	30	24.5	7.2	2.9	9.4	3.6	2.1	2.1	4.8	2.1	0.50	0.20	1.6	0.6413	0.7786	0.5040
Hunter Hale	BAHC	2025-26	33	20.2	8.6	2.2	11.5	3.8	1.9	0.4	1.9	2.5	0.80	0.20	1.5	0.6402	0.6689	0.6114
Royce Hamm, Jr.	TRA	2025-26	27	24.8	7.5	2.4	9.7	3.8	1.7	1.6	4.2	0.9	0.50	0.70	1.9	0.6399	0.7416	0.5381
Tarik Biberovic	FEN	2025-26	34	24.0	9.0	1.1	12.6	4.5	1.0	0.7	2.8	2.0	0.30	0.10	1.5	0.6201	1.0000	0.2401
Michal Sokolowski	PIN	2025-26	23	26.6	6.5	2.8	10.7	3.3	2.6	1.2	3.4	1.4	1.20	0.10	1.2	0.6154	1.0000	0.2308
Cameron Young	PIN	2025-26	28	25.2	11.0	5.7	17.0	5.1	4.7	0.6	2.5	1.4	0.60	0.10	1.3	0.6127	1.0000	0.2254
Shane Larkin	EFE	2025-26	13	27.6	9.2	4.0	13.9	4.2	3.5	0.7	2.0	5.5	1.50	0.10	2.4	0.6090	0.6530	0.5649
Charles Manning, Jr.	PIN	2025-26	30	28.4	11.0	2.8	13.6	5.2	2.4	0.5	2.6	2.9	0.70	0.50	1.7	0.5979	0.6337	0.5621
Michael Devoe	TUR	2025-26	27	20.4	6.9	2.4	9.4	3.4	1.7	0.5	1.8	3.5	1.10	0.10	1.6	0.5924	0.4319	0.7529
P.J. Dozier	EFE	2025-26	26	20.0	8.2	1.5	10.1	3.8	1.2	0.5	2.5	2.7	0.80	0.10	1.2	0.5833	0.6643	0.5023
Tre'Shawn Thurman	ENEN	2025-26	29	19.6	6.0	1.9	7.9	2.6	1.5	0.7	1.9	0.9	0.50	0.20	0.7	0.5691	0.6220	0.5162
Roberts Blumbergs	SOC	2025-26	30	25.2	6.8	1.1	8.6	3.1	0.7	0.9	3.7	0.6	0.50	0.20	1.1	0.5669	0.8112	0.3226
Uros Trifunovic	TUR	2025-26	22	22.0	7.2	1.4	9.4	3.2	1.1	0.6	1.9	1.0	0.70	0.10	0.6	0.5665	0.6860	0.4470
Evan Bruinsma	DEM	2025-26	22	24.9	8.5	2.5	10.6	4.0	1.7	1.6	3.7	1.5	0.70	0.20	1.0	0.5655	0.7393	0.3917
Jalen Lecque	DEM	2025-26	24	27.2	11.8	4.5	15.7	5.3	3.3	1.0	2.4	2.0	0.80	0.30	1.9	0.5609	0.6766	0.4453
Yigitcan Saybir	TOF	2025-26	27	28.1	7.7	3.0	11.0	4.1	1.9	1.8	3.0	1.9	1.10	0.20	1.5	0.5592	0.7450	0.3733
Devon Hall	FEN	2025-26	30	23.4	6.8	2.4	9.4	3.0	2.1	1.0	2.4	3.4	0.50	0.10	1.7	0.5454	0.7192	0.3715
Yigit Onan	MANI	2025-26	30	28.0	8.3	3.8	11.0	3.8	2.7	1.6	3.3	2.0	0.90	0.20	1.6	0.5358	0.6977	0.3739
Malachi Flynn	BAHC	2025-26	33	29.4	12.1	3.5	15.7	5.3	2.7	0.6	2.3	4.9	1.40	0.10	2.0	0.5290	0.6140	0.4440
Stanley Whittaker	SOC	2025-26	23	27.0	10.9	1.7	13.1	5.1	1.3	0.5	1.8	3.5	0.70	0.10	1.8	0.5205	0.7487	0.2923
David Efanayi	SOC	2025-26	29	30.8	10.7	3.9	14.6	4.7	3.3	0.6	1.8	5.1	0.60	0.20	3.2	0.5093	0.5573	0.4614
Yannick Franke	SOC	2025-26	29	26.3	10.5	4.3	14.7	4.2	4.0	0.6	3.0	1.6	0.70	0.00	1.8	0.7649	1.0000	0.5297
Pako Cruz	MER	2025-26	29	26.0	10.7	1.1	13.3	4.9	0.8	0.7	1.7	4.0	1.00	0.00	2.8	0.8073	1.0000	0.6145
Sam Griffin	MERK	2025-26	29	19.9	9.5	1.9	12.0	4.4	1.8	0.2	1.3	1.3	0.50	0.00	1.4	0.7556	1.0000	0.5111
Joseph Girard III	TRA	2025-26	10	17.6	7.9	0.5	9.7	3.4	0.3	0.3	1.0	2.5	0.90	0.00	1.5	1.0000	1.0000	1.0000
Caleb Homesley	BAHC	2025-26	32	23.2	9.4	3.4	11.8	3.9	2.6	0.4	2.6	2.6	1.00	0.30	1.8	0.4986	0.3763	0.6210
Yavuz Gultekin	BURS	2025-26	16	25.8	8.8	2.3	10.2	3.9	1.6	1.9	3.5	1.0	0.50	0.10	0.9	0.4893	0.7645	0.2141
Bryant Crawford	BURS	2025-26	21	20.2	8.3	3.1	10.9	3.3	2.5	0.2	1.3	3.3	0.90	0.20	1.5	0.4879	0.2441	0.7317
Marcus Georges-Hunt	BURS	2025-26	10	25.1	8.3	2.9	13.1	4.5	2.3	0.5	2.2	1.9	0.90	0.20	1.1	0.4877	0.5709	0.4044
Isaia Cordinier	EFE	2025-26	13	22.8	8.0	3.0	10.8	3.7	2.5	0.8	2.7	3.2	0.50	0.10	1.9	0.4863	0.5995	0.3731
Will Cummings	GAL	2025-26	12	27.5	9.7	3.4	12.3	4.3	2.8	0.8	2.5	4.4	1.30	0.10	2.6	0.4788	0.5840	0.3736
Akwasi Abeyie Yeboah	TRA	2025-26	32	24.5	7.0	2.1	9.9	3.2	1.7	1.0	3.2	1.4	1.00	0.10	1.3	0.4681	0.6897	0.2465
Scoochie Smith	MANI	2025-26	30	31.1	10.2	3.6	11.6	3.4	3.0	0.4	2.4	6.1	1.30	0.10	2.5	0.4546	0.3519	0.5574
Roko Badzim	MERK	2025-26	30	25.7	8.4	2.1	11.5	3.9	1.7	0.6	1.8	3.1	0.70	0.10	1.5	0.4384	0.5801	0.2968
Markel Starks	MANI	2025-26	14	24.9	7.4	1.0	9.3	3.4	0.7	0.1	1.8	4.8	1.00	0.10	1.6	0.4379	0.2592	0.6166
Stefan Moody	PIN	2025-26	21	29.9	9.1	2.8	11.2	3.6	2.4	0.4	2.8	4.5	0.80	0.20	3.0	0.4342	0.3824	0.4861
Jordan Usher	TUR	2025-26	30	22.9	7.3	2.0	10.1	3.8	1.4	0.6	2.7	1.4	1.10	0.10	1.1	0.3994	0.5244	0.2743

Judah Mintz	MANI	2025-26	24	25.7	10.3	6.3	15.1	5.0	4.8	0.4	1.9	2.1	1.30	0.00	1.7	0.7089	0.7774	0.6404
Jermaine Love-Roberts	ENEN	2025-26	32	23.2	7.2	2.7	10.1	3.4	2.4	0.5	1.6	2.0	0.90	0.10	1.7	0.3887	0.4989	0.2786
Jonah Mathews	BES	2025-26	35	24.8	11.1	2.7	13.5	4.7	2.2	0.3	2.1	2.5	1.20	0.10	2.1	0.3506	0.4136	0.2876
Hugo Besson	TOF	2025-26	30	23.7	8.4	3.5	12.0	3.7	2.9	0.4	2.9	1.8	0.80	0.10	1.4	0.3428	0.4135	0.2721
Malik Parsons	BURS	2025-26	18	25.3	8.4	3.3	11.6	4.0	2.8	0.4	1.3	2.3	1.30	0.10	2.3	0.3317	0.4097	0.2537
P.J. Pipes	DEM	2025-26	28	24.5	10.7	2.0	13.6	4.9	1.7	0.3	1.4	2.1	0.40	0.00	2.2	0.4884	0.5862	0.3905
Jordan Loyd	EFE	2025-26	31	24.3	8.9	3.2	12.9	4.0	2.7	0.6	2.3	1.9	1.00	0.00	1.2	0.6420	0.5862	0.6978
Jaleen Smith	TUR	2025-26	30	26.6	9.9	2.9	12.2	3.7	2.6	0.5	2.0	3.5	0.90	0.00	1.7	0.5821	0.5134	0.6507
Brynton Lemar	BES	2025-26	31	20.8	6.9	2.7	10.1	3.2	2.1	0.6	0.9	2.5	0.60	0.00	1.0	0.5543	0.5043	0.6044
Jordon Crawford	ENEN	2025-26	31	25.5	12.2	3.6	14.5	4.9	3.1	0.4	1.5	5.7	0.90	0.00	2.0	0.6605	0.4995	0.8215
Justin Cobbs	MER	2025-26	16	23.1	8.1	3.7	10.6	3.3	3.2	0.3	1.2	3.6	0.40	0.00	1.6	0.4462	0.4030	0.4895
Furkan Korkmaz	TOF	2025-26	23	19.6	7.2	2.8	9.0	3.0	1.9	0.3	1.9	1.4	0.60	0.00	1.0	0.4915	0.2810	0.7020
Jordan Floyd	TOF	2025-26	12	18.5	7.7	2.4	9.0	3.2	2.0	0.2	0.9	2.3	0.80	0.00	1.8	0.4660	0.2619	0.6700