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Abstract

Professional sports teams employ highly paid managers and coaches to train players and make tactical and strategic team decisions. A large literature analyzes the impact of manager decisions on team outcomes. Empirical analysis of manager decisions requires a quantifiable proxy variable for manager decisions. Previous research focused on manager dismissals, tenure on teams, the number of substitutions made in games, or the number of healthy players on rosters held out of games for rest, generally finding small positive impacts of manager decisions on team success. We analyze manager decisions by developing a novel measure of game-specific coach decisions based on a Herfindahl-Hirschman Index (HHI) of playing-time distribution across players on a team roster in a game. Evidence from two-way fixed effects regression models explaining observed variation in National Basketball Association team winning percentage over the 1999-2000 to 2018-2019 seasons show a significant association between managers allocation of playing time and team success. A one standard deviation change in playing-time HHI that reflects a flattened distribution of player talent is associated with between one and two additional wins per season, holding the talent of players on the team roster constant. Heterogeneity exists in the impact across teams with different player talent. This is one of the first papers to examine playing time concentration in professional sports. Our results are important for understanding how managerial decisions affect the production of wins in team sports.

Key words: coach performance; win production; National Basketball Association; Herfindahl Hirschman Index

JEL Codes: D8, I10, I18, L2; Z2

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Introduction

In team sports, managers or coaches make strategic and tactical decisions in terms of the composition of game rosters, allocation of playing time within games, player actions on the court or field, and other aspects of play. Team managers exert substantial influence on games and seasons, earn high salaries, and occupy a highly visible position. Given this importance, a large body of literature in sports economics assesses the importance of managers in determining team success.

Analyzing the impact of manager's decisions on team outcomes faces several empirical challenges. Quantification of managerial decisions represents one important issue. Team outcomes and player inputs can be quantified but decisions made by managers cannot. Previous empirical research exploited changes in managers or coaches (Berri et al., 2009; Goff et al., 2019) or managerial tenure (Frick & Simmons, 2008; Koschmann, 2019) to analyze the impact of manager's decisions on team success. Analyzing changes in managers leverages the exposure of the same set of players to different managers. Analyzing managerial tenure exploits variation in the amount exposure players receive from managers. A related approach directly analyzes the impact of manager or coach changes on individual player performance (Bradbury, 2017; Pitts & Evans, 2019; Allen, 2021).

More recent research exploits variation in the players appearing on the field or court in individual games (Rohde & Breuer, 2017; Arcidiacono et al., 2017), player substitutions during games (Kordyaka et al., 2022) or decisions to not use players in games (Scoppa, 2015; Rohde & Breuer, 2017; Gong et al., 2022; Hoey et al., 2023) to analyze the impact of manager decisions. Team managers make decisions about playing time and active rosters in each game over the course of a season, so the variables identified above represent a cleaner proxy for managers decisions than manager fixed effects or tenure.

Some economic models of managerial effectiveness emphasize their role in coordinating and utilizing available team resources like players (Goff et al., 2019). Little evidence exists that in-game decisions about player utilization affect team success, despite season-level evidence supporting the importance of managers. Kordyaka et al. (2022) found that more player substitutions by managers reduced the probability that a team won a game, increasing the tension in this literature.

We contribute to the economic literature analyzing managerial effectiveness by developing a novel proxy variable for game level manager decisions. Using detailed data on the number of seconds each player on a National Basketball Association (NBA) team's roster played in each NBA regular season game over the 1999-2000 through 2018-2019 seasons, we calculate Herfindahl Hirschman Indexes (HHIs) of the playing time across players on team rosters in each regular season game. These indexes directly reflect in-game manager decisions on the utilization of available team resources. We aggregate the game level variables to the team-season level by calculating the average value of the HHIs and a variable reflecting the average quality of players on the team's roster in each game over each regular season game to match the level of aggregation used in the literature. We analyze the association between these team-season variables and each team's regular season success measured by win percentage using a two-way fixed effects regression model.

The results indicate that teams managed by a coach who employs a more equal distribution of playing time across players on the roster win more games than teams managed by coaches who concentrate playing time among a smaller group of players, controlling for average roster quality. Results also show heterogeneity in the impact of manager decisions about the distribution of playing time across teams with different levels of player talent. Playing time allocation decisions made by managers of teams with more talent on the roster are associated with larger changes in team success than decisions made by managers of teams with less talent.

Theoretical Context and Related Literature

A team win production function lies at the heart of research on managerial decisions. The theory posits that sports teams produce wins using inputs from both players and team managers. Berri et al. (2009) contains a detailed discussion of the role played by team coaches or managers in the production of wins along with a model of coach effectiveness. A basic view of the role of managers in the win production function treats them as another input to production like player inputs. Berri et al. (2009) characterized sports team managers as entrepreneurs who exploit market inefficiencies, for example the undervaluation of on-base-percentage in Major League Baseball, or develop novel, disruptive strategies like the air raid offense in American football. This entrepreneurial ability makes players more productive, increasing team success.

Goff (2013) and Goff et al. (2019) extended the line of research on win production using both player and manager inputs by including team managers, general managers, and owners as inputs. These papers emphasize the idea that managers affect the technology through which player inputs produce wins. Goff et al. (2019) also articulated a resource-based theoretical perspective on the role of managers in which they coordinate the utilization of other inputs in the production function, bundle available resources for production, or engage in creative utilization of productive resources. The latter actions echo the entrepreneurial role played by managers in Berri et al. (2009).

We develop a proxy variable for manager's decisions about the organization of resources in games and use this to explain variation in team success. Quantifying coaching decisions in a way that separates resource-based decisions from entrepreneurial activities, as well as distinguishing the impact of manager decisions from player quality or ability, represents a key issue in this literature.

The empirical literature contains three approaches for quantifying managerial inputs to sports team win production: analyzing the impact of changes in managers on team success, analyzing the impact of managerial tenure on team success, and analyzing the impact of player exposure to different managers through managerial changes or player movement across teams on individual player performance. These papers assume that managers represent an input to production or engage in entrepreneurial behavior to affect team success.

In general, papers in this literature use proxy variables that do not directly quantify manager's decisions in terms of resource utilization, for example exploiting in-season changes in managers, an indirect proxy variable for manager decisions that assumes the new manager makes different decisions than the previous manager. While this literature contains a large number of papers and spans decades, we only review the most recent contributions that relate to this paper. Interested readers can consult the papers cited here for reviews of earlier work.

De Paola & Scoppa (2012) analyzed the impact of different managers on the performance of professional football teams in Serie A in Italy over the 1997 to 2008 seasons using an indicator variable identifying teams that changed their manager during the season. Points over the season and goal differential increased when teams changed managers, but the paper also identifies the presence of an "Ashenfelter Dip," a decline team in performance prior to managerial changes, suggesting endogeneity of changes in managers in that these changes occur because of unobservable factors associated with team performance. Coaching changes did not affect team performance after accounting for the decline in team performance prior to managerial dismissals.

Goff (2013) investigated the impact of managers on the performance of Major League Baseball (MLB) teams over the 1970 to 2011 regular seasons using manager fixed effects to quantify the impact of managers on team performance. Results from hierarchical fixed effects regression models showed that 8.5% of the observed variation in team winning percentage was explained by between and within variation in managers. The within variation reflected managers changing teams during the sample period.

Goff et al. (2019) extended this analysis by using a dynamic lag adjustment model to account for differences in the impact of a manager's decisions over time, again using manager fixed effects to capture managerial ability and decisions. Results from this model show that team winning percentage increased in the first five years after a new manager took over a team.

Buzzacchi et al. (2021) analyzed the impact of managers on total team points earned by teams in Serie A in Italy over the 1998 to 2018 seasons using manager fixed effects to capture manager decisions. Results from OLS regression models, Shorrocks-Shapley variance decompositions, and the data envelopment analysis approach found that managers increase team points scored.

These papers generally find evidence that managers affect team outcomes at the season level. However, the use of manager fixed effects to capture managerial decisions limits the ability for the analysis to identify mechanisms through which managers impact team performance. Also, the endogeneity of manager dismissals identified by De Paola & Scoppa (2012) makes the interpretation of within-manager variation on team success difficult to
interpret.

A second line of research exploits variation in the tenure of managers at different sports teams to quantify managerial inputs to win production. Frick & Simmons (2008) analyzed the impact of manager tenure, career wins by the manager, and firing managers on the total number of points earned by professional football teams in the German Bundesliga 1 over the 1981 to 2003 seasons. Results from stochastic production frontier models showed that managers with longer tenure at teams and more career wins increased the efficiency of win production on their teams. Manager dismissals reduced the efficiency of win production.

In a similar vein, Hall & Pedace (2016) analyzed the impact of managers on season winning percentage for MLB teams over the 1985 to 2010 seasons. This paper also quantified manager inputs using the number of seasons a manager coached each team and the manager's career winning percentage. results from a two-way fixed effects regression model found no relationship between manager tenure or career winning percentage on team performance.

Koschmann (2019) analyzed the impact of manager tenure on the performance of individual quarterbacks in games played in the 2008 to the 2016 National Football League (NFL) regular season. The paper used quarterback rankings on a -2 to +2 scale generated by three experts grading the performance of each quarterback by watching each game that the quarterback appeared in. results from Hierarchical Bayesian regression models showed that quarterback performance on the −2 to +2 scale improved with head coach tenure with the team.

Analyzing the impact of managers on player performance moves the literature closer to identifying mechanisms through which managers affect team performance. A seminal paper in the literature on managerial inputs to production, Berri et al. (2009), undertakes an empirical analysis of the role played by managers in sports team win production by NBA teams over a season for the 1977 through 2007 seasons.

This paper estimates OLS regression models explaining variation in a player performance variable, adjusted production per 48 minutes, a summary index of a number of player performance variables like shots made and missed, rebounds, assists, turnovers, steals, and blocked shots adjusted to reflect the players contribution over 48 minutes of play in NBA games. The regression models contain manager fixed effects to quantify the effects of managers on player performance, along with an indicator variable for changes in manager within each season. The results identify specific managers as exerting a positive impact on player performance.

Bradbury (2017) analyzed the impact of managers on the performance of MLB players over the 1980 through 2009 seasons. Proxy variables for manager's inputs included both manager fixed effects and a variable reflecting the number of years each manager coached each MLB player. The results from two-way fixed effects models explaining observed variation in pitcher's ERA and position player's OPS found no evidence that manager's inputs affected player performance.

Pitts & Evans (2019) analyzed the impact of managers on the performance of 133 NFL quarterbacks over the course of a season, in terms of five different quarterback performance variables. Variables capturing manager inputs included the number of years a quarterback was coached by specific head coaches and offensive coordinators, offensive coordinator fixed effects, and changes in both head coaches and offensive coordinators. results from fixed effects and random effects regression models revealed no evidence that manager inputs impacted quarterback performance. However, a hand full of the offensive coordinator fixed effects were statistically different from zero, indicating the presence of some relationship between coaching and player performance.

Allen (2021) analyzed the impact of changes in a specialized manager, the goalie coach on National Hockey League (NHL) teams, on the performance of NHL goaltenders (goalies) in terms of goals scored against average and save percentage over the 2007 through 2018 NHL seasons. Results from a propensity score matching approach that matched goalies on teams that changed to goalies that did not change coaches showed that the performance of goalies exposed to different coaches showed improved performance after the coaching change.

While manager fixed effects generate both between and within variation in the exposure of players to managers, the endogenous nature of manager dismissal complicates the interpretation of these fixed effects. And the possible presence of an “Ashenfelter Dip” in team performance before changing coaches also complicates the assessment of the impact of manager inputs on player performance.

This paper also contributes to recent research that focuses on substitution patterns and within season changes to players on team’s active rosters in professional sports. The presence of incentive for teams to intentionally lose games, called “tanking” (Taylor & Trogdon, 2002), motivates much of this research. Tanking refers to tournament incentives generated by the presence of reverse-order player entry drafts in professional sports leagues that reward losing teams with earlier picks in the next entry draft. Analysis of player substitutions and active roster changes represents an approach to identifying resource-based mechanisms through which teams can intentionally lose games by fielding a squad of less talented players and resource based managerial decisions that increase team success.

Rohde & Breuer (2017) analyzed changes in the lineups employed by managers of 31 German Bundesliga 1 clubs in 3,060 football matches played from 2006 to 2015. The paper used the market value of the players selected from the active roster for each game based on player market values generated by the German web site Transfermarkt as a proxy for the quality of the starting lineup selected by the team manager in each game. Results from two-way fixed effects regression models showed that managers used less talented starting lineups in matches when important team objectives like winning the league championship and qualifying for the UEFA Champions League (UCL) had been achieved. Managers also selected less talented starting lineups in matches played shortly before upcoming UCL matches.

Arcidiacono et al. (2017) analyzed play-by-play data from NBA regular season games during the 2006-2009 regular season to determine the impact of changes in specific players on the floor on the outcome of individual offensive possessions based on a complex, nonlinear win production model. The paper identifies all sets of offensive and defensive players on the court on each possession which allows for the identification of both own-player inputs and spillover effects across players on the floor. The empirical models include coach fixed effects to control for the impact of managers on the composition of players on the court, but the estimates on these variables are not reported because the paper focuses on spillovers between players on the same team. The paper contains evidence of positive productivity spillovers in the production process. The results in this paper emphasize the importance of team resource-related manager decisions in the production of wins by sports teams.

Fornwagner (2019) analyzed variation in the amount of playing time managers assigned to individual players in NHL games, and the number of substitutions made by managers during games for the 1988 through 2016 regular seasons. Results from two-way fixed effects regression models showed that managers allocated more playing time to less talented players after their teams were eliminated from playoff contention.

In a closely related paper, Gong et al. (2022) analyzed factors associated with the decision to rest healthy NBA players by removing them from the active roster for specific games. Like Fornwagner (2019), this paper exploits elimination from post season play as an exogenous change in the incentives for teams to win games. Results from Poisson regression models indicate that NBA managers are more likely to rest healthy players after their teams were eliminated from post season play.

Finally, in another closely related paper Kordyaka et al. (2022) analyzed the causal impact of player substitutions made by NBA managers over three-minute periods in NBA games played in the 2006 through 2017 seasons on team success. Team success variables included the difference in points scored by teams over the three-minute period and an indicator variable for the team with the higher score at the end of each three-minute time period. Results from an IV model using opposing team substitutions as an instrument find that more substitutions during a period reduced team performance during that period.

These papers show that manager decisions about which players appear in games, and how long players appear in games affect team performance. They also show that player substitutions made by managers affect team success in games. Team rosters contain players with different levels of ability or talent. Managers decide on how to best allocate this talent or ability by varying the composition of players appearing in games. These variables reflect actual decisions made by managers about playing time, rather than changes in player's exposure to managers through dismissal or manager tenure. This advances the understanding of the mechanisms through which managers affect team success and the role that managers play in the win production process.

Empirical Analysis

We analyze the relationship between decisions about playing time made by team managers and NBA team success. Developing proxy variables for manager decisions and understanding the consequences of manager's decisions about playing time in terms of team success represents important contributions to the literature assessing managerial effectiveness. Because much of the literature on managerial inputs discussed above aggregates variables to the team-season level, we also employ this level of aggregation in our analysis data set. The goal is to analyze the association between our novel variable reflecting manager decisions about the allocation of playing time and team success, holding the quality of the team and the team's opponents constant.

Limits on the number of players on NBA rosters, the rule limiting teams to only five players for each team on the floor at any time, and the length of NBA games constrain managers decisions about the allocation of playing time in each game and over the course of the NBA season. Factors outside of the direct control of the coach like players in foul trouble in a game may also impact the distribution of playing time in a game. Injuries impact the impact of playing time across games in a season.

The allocation of playing time by the manager of an NBA team impacts both the talent of the player inputs on the floor over any period of time and, potentially, the level of fatigue experienced by players, under the assumption that player fatigue increases with seconds played. The relationship between the allocation of playing time and NBA player fatigue could be complex, depending on in-game decisions. The fact that NBA players are elite athletes with training regimens designed to maximize their performance potential over the course of a season clearly complicates the relationship between playing time and fatigue.

Papers that analyze play-level or within game personnel decisions (Arcidiacono et al., 2017; Kordyaka et al., 2022) identify several factors that might affect the allocation of team resources within a game. Existing research on employee working time and productivity shows that increasing working time leads to higher levels of work fatigue, work stress, and employee errors. Becker & Murphy (1992) show that increasing the number of co-workers on team projects generates coordination costs that reduce worker productivity. Arcidiacono et al. (2017) show that specific players generate larger spillover benefits to their teammates when they are on the floor, increasing team productivity.

Allocation of playing time can also affect the risk that an NBA player experiences an injury, leading to a reduction in playing talent available in future games. Increasing the playing time by a player exposes that player to increased injury risk, both due to injuries while playing and injuries from limiting rest. The sports medicine literature refers to strategies aimed at reducing this risk as “load management” (Gabbett, 2020). We argue that playing time concentration reflects the injury risk faced by a team, establishing a mechanism between our concentration measures and team performance.

Thus, managers face a trade-off when allocating playing time across players in that a less concentrated distribution of playing time reduces the impact of fatigue on player productivity but this also increases coordination costs and reduces the time that players with large productivity spillover effects spend on the floor with their team mates. Teasing out these complex relationships lies outside the scope of this paper. Our HHI measures of the distribution of playing time reflect both coach decisions, factors outside the coach’s control like foul trouble, and injuries. The reduced form parameter estimates in our regression models assume that the actual distribution of playing time reflects decisions made by coaches and reflect the overall impact of positive and negative effects of increasing concentration of playing time on player productivity.

Data Sources and Variables

We collected data on NBA teams, games, and players from basketball-reference.com over the 1999-2000 to 2018-2019 seasons. We collect season level Value Over Replacement Player (VORP) measurements for each player in each season. Game level information about managerial decisions come from box score data where playing time is recorded for each player along with performance statistics. We also collect information about coaching turnover for each team and season.

We analyze the impact of player and managerial inputs on the production of total team wins in a season. The primary data set contains panel data at the player-game-team-season level. Although we collect data on player performance in individual NBA games, the analysis data set aggregates all variables to the team-season level in keeping with other papers in the literature. To describe the primary data set, let t index NBA seasons, $j = 1,...,J_t$ index NBA teams, and $g = 1,...,G_{jt}$ index NBA regular season games.

Let $i \in R_{gjt}$ identify individual players on team j's official team roster R_{gjt} in game g played in season t. A team's current roster can contain both active players, A_{jts}, and inactive players I_{jts} in game j, which are sets that partition the roster R_{gjt}. Current NBA rules and conditions specify $J_t \equiv 30$, $G_{jt} \equiv 82$, and $|R_{gjt}| \equiv 15$. Let j' refer to the opponent of team j in game g. Because team j' cannot play against itself g' identifies the game team in which team j' plays against team j.

We construct a measure of player contributions to the production of wins by NBA teams using the Value Over Replacement Player (VORP) estimate for each player i over season t. VORP represents a standard, widely used measure of the quality of an NBA player in the literature (Burdekin & Van, 2018; Humphreys & Johnson, 2020; Kaplan, 2022; Paulsen, 2022). VORP reflects an estimate of the number of points per 100 NBA team possessions that player i contributed to his team above the contribution that would be made by a replacement-level ($VORP_{it} = -2.0$) NBA player, based on box score statistics. VORP is measured relative the average NBA team and scaled to reflect an 82-game season.

We refer to our measure of player inputs, $talent_{gjt}$, as team talent or quality. We define team j's talent used in game g played in season t as the seconds-played weighted average VORP of all players on team j's active roster in game g. Specifically,

$$talent_{gjt} = \sum_{i \in R_{gjt}} s_{igjt} VORP_{it}$$

where

$$s_{igjt} = \frac{sec_{igjt}}{\sum_{\ell \in R_{gjt}} sec_{\ell gjt}}$$

is player *i*'s share of playing time computed as total seconds played in each game, sec_{igjt}.

Note that $VORP_{it}$ is constant for each player in all games in season *t*. This means within-season variation in $talent_{gjt}$ for team *j* (variation across games) is driven primarily by the playing time choices made by coaches, reflected in the playing-time shares s_{igjt} for each player in each game, and secondarily by player movement across teams within seasons, captured in R_{gjt}.

We define the "opponent talent" of team *j* in game *g* of season *t* as

$$talent_{gjt}^{Opp} = \sum_{i \in R_{g'j't}} s_{ig'j't} VORP_{it} \equiv talent_{g'j't}$$

where j' and g' index *j*'s opponent in each game. We compute this value to account for both the quality of opponents played each season and the impact of strategic incentives on managers' playing time decisions in games. Note that the unbalanced NBA regular season schedule and different player substitution patterns against different teams generates variation in the average level of $talent^{Opp}_{gjt}$ across teams in each season.

We also calculate variables related to the distribution of playing time across players and player talent in games and include them in the regression models. These variables reflect managers' in-game decisions since the manager controls when and how long each player on the roster appears in each game. We measure the concentration of playing time and talent on team *j* for each game *g* in season *t* using Herfindahl–Hirschman Indexes (HHIs) based on

$$sec_{gjt}^{HHI} = \sum_{i \in R_{gjt}} s_{igjt}^2$$

$$talent_{gjt}^{HHI} = \sum_{i \in R_{gjt}} \left(\frac{s_{igjt} VORP_{it}}{talent_{gjt}} \right)^2.$$

The first variable, sec^{HHI}_{gjt}, is the HHI reflecting concentration of playing time across players on team j in game g in season t.[2] Theoretically, this concentration index falls in the range $\left[\frac{1}{13}, \frac{1}{5}\right]$.[3] sec^{HHI}_{gjt} reflects in-game decisions by coaches about which five of the available players appear in the game and how much time each player spends on the floor.

The variable $talent^{HHI}_{gjt}$ measures the concentration of available team talent employed by the manager in each game. Formally, this is the HHI of the seconds-played weighted-average VORP of members of team *j*. In other words, interpreting the quantity $s_{igjt} \times VORP_{it}$ as the input contributed by player *i* in game *g* to team win production, $talent^{HHI}_{gjt}$ reflects the concentration of player talent on team *t* in game *g*. Compared to sec^{HHI}_{gjt}, which measures the concentration of playing-time in a given game, $talent^{HHI}_{gjt}$ instead reflects the concentration of player ability inputs in each game. We know $talent_{gjt}^{HHI} \in \left[\frac{1}{13}, 1\right)$, where this value approaches 1 asymptotically as the total VORP on the team is concentrated in a single player.

Example: Consider two hypothetical teams, each with only 5 players. By definition

$$sec_{1jt}^{HHI} = sec_{2jt}^{HHI} = 5 \cdot \left(\frac{1}{5}\right)^2 = \frac{1}{5}$$

since every player must play full time. Suppose $VORP_{it} = 1$ for every player *i* on team 1—then,

$$talent_{g1t} = 5 \cdot \left(\frac{1}{5} \cdot 1\right) = 1$$

[2] HHI is a cornerstone concept in antitrust economics, industrial organization, and measurement of competitive balance in sports leagues that measures concentration of variables like wins across teams (Szymanski, 2003; Berry, Gaynor, & Morton, 2019). In the antitrust context, HHI is the sum of squared market shares across firms and reflects, on a scale from 0 to 10000, level of concentration or dispersion of the observed market shares. The U.S. Department of Justice Antitrust Division and Federal Trade Commission use HHIs to identify illegal mergers, where a merger increasing a market's HHI by more than 100 carries a "structural presumption" of anticompetitive outcomes.

[3] The minimum possible value for sec^{HHI}_{gjt} is $1/|A_{gjt}|$, where $A_{gjt} \subset R_{gjt}$ is the set of all active players on the team. This occurs when all active players share an equal amount of playing time. The maximum possible value of sec^{HHI}_{gjt} is observed when only 5 players on a team have non-zero playing time in a game, each with $s_{igjt} \equiv 1/5$ of the seconds in the game, so the maximum value of sec^{HHI}_{gjt} is $1/5$.

$$talent^{HHI}_{g1t} = 5 \cdot \left(\frac{\frac{1}{5} \cdot 1}{1}\right)^2 = \frac{1}{5}$$

Note that these talent and talent concentration values were achieved with equal playing-time shares and with a total team VORP of 5.

For team 2, let $VORP_{it} = 3$ for one player and $VORP_{it} = 1/2$ for the other four players. Then,

$$talent_{g2t} = \left(\frac{1}{5} \cdot 3\right) + 4 \cdot \left(\frac{1}{5} \cdot \frac{1}{2}\right) = 1$$

$$talent^{HHI}_{g2t} = \left(\frac{\frac{1}{5} \cdot 3}{1}\right)^2 + 4 \cdot \left(\frac{\frac{1}{5} \cdot \frac{1}{2}}{1}\right)^2 = \frac{2}{5} > \frac{1}{5}$$

Note that for team 2, team total VORP, talent, and playing-time shares are all identical to team 1. However, because the player with $VORP_{it} = 3$ is six times as productive on the court per second as their teammates, talent concentration $talent^{HHI}_{g2t}$ is twice as large, but playing time concentration and the level of team talent itself are no different than the case with equal playing time. Our overarching argument follows directly from this example: team success is a function of both talent level, $talent_{gjt}$, and talent concentration, $talent^{HHI}_{gjt}$. Two rosters with the same average level of talent chosen by their respective coaches may nonetheless have unequal chances of team success—concentration measures sec^{HHI}_{jt} and $talent^{HHI}_{jt}$ may both uniquely determine team success as well.

These variables reflect coaching decisions and differ from other approaches used by related papers in the literature. Gong et al. (2022) analyzed decisions to rest players in games which will be reflected in the roster for each team in each game R_{gjt}. Kordyaka et al. (2022) analyzed variation in the number of substitutions made in a game by each team. Both HHIs increase monotonically with the number of substitutions made in a game, since more substitutions result in fewer seconds of playing time for each player.

Again, we aggregate data from the game-team-season level to the team-season level by averaging across games. For the player talent variable

$$talent_{jt} = \frac{1}{G_{jt}} \sum_{g=1}^{G_{jt}} talent_{gjt}$$

is the average playing talent on team *j* in season *t* over all *G* regular season games, and similarly define team-season averages for all other variables. We analyze team-season level variation for practical reasons in that we have a long panel (20 seasons) and enough teams to generate substantial cross-sectional variation, 29 or 30 teams per season, to generate sufficient statistical power to identify regression coefficients, even in a saturated two-way fixed-effects model, and to make our results directly comparable to the existing literature on managerial inputs to team win production which primarily uses data aggregated to this level.

	# Unique Obs.	Mean	S.D.	Min.	Median	Max.
# of Teams (per season)	2	29.76	0.43	29.00	30.00	30.00
Total # of Games	3	81.19	3.50	66.00	82.00	82.00
Total # of Wins	58	40.59	12.39	7.00	41.00	73.00
Total # of Losses	57	40.59	12.39	9.00	40.00	72.00
Win %	80	50.00	15.09	10.61	51.22	89.02
# of Days between Games	14	2.07	0.05	1.86	2.07	2.17
Coach Changed	2	0.13	0.33	0.00	0.00	1.00
Talent	595	3.88	0.64	2.27	3.87	5.51
Opponent Talent	595	3.88	0.13	3.47	3.90	4.17
Playing Time Concentration	595	0.12	0.007	0.10	0.12	0.14
Talent Concentration	595	0.15	0.02	0.11	0.15	0.25

Table 1: Summary Statistics. This table shows summary statistics for the team-by-season panel of aggregated performance data. There are 595 total observations: 29 observations in seasons 1999-2000, 2000-2001, 2001-2002, 2002-2003, and 2003-2004 and 30 observations in 2004-2005 to 2018-2019 following the addition of the Charlotte expansion team.

The decision to aggregate data to the season level is also based on two important conceptual reasons. First, we note that the empirical relationship between two variables at the game level is related to, but not necessarily prescriptive of the relationship between those two variables at the season level. This means that, in the case of playing time concentration and talent concentration, an analysis of the game level effect of playing time distribution on game outcomes yields conclusions that answer a different research question regarding coach influence than the present analysis at the season level.

A second reason to leave game level analysis to future research and instead focus on a season level analysis is that the former represents a more complicated empirical environment due to game-to-game varying incentives. Unobserved heterogeneity in the incentives faced game-to-game within a season make formal causal inference and even structural econometric modelling possible tools for inference in a game level setting. This heterogeneity is effectively averaged out in season level data, and we can instead directly control for a team's competitive environment in a given season.

Table 1 contains summary statistics for the aggregated team-by-season analysis data set. The variation in the unique number of observations across variables comes from both the 2004 NBA expansion and the 2011-2012 lockout which shortened the regular season to 66 games. The team talent measures and the HHIs for playing time and player talent represent the key variables of interest since other papers in the literature do not use this approach to measuring team talent and managers' decisions. The average player contributed about 5 points over the contribution that would have been made by a replacement level player (*VORP* = −2) for each 100 team possessions in games played, adjusted for the actual number of seconds played by each player. Note that the opponent talent variable distribution contains substantially less variation than the own team talent variable distribution. The standard deviation of the talent input variable, 0.64, is more than four times larger than the opposing team talent variable, 0.13.

Recall that $\left[\frac{1}{13}, \frac{1}{5}\right]$, roughly 0.08 to 0.20, bounds the playing time concentration variable. The mean of this distribution, 0.12, falls below the midpoint of the theoretical bounds, 0.14 with a tightly clustered distribution, standard deviation 0.007. The largest observed playingtime concentration value is at the midpoint of the $\left[\frac{1}{13}, \frac{1}{5}\right]$ interval. The interval $\left[\frac{1}{13}, 1\right)$ bounds the talent concentration variable, although the upper bound value would only be observed asymptotically. The actual talent distribution is more concentrated than the playing time concentration distribution, on average. The talent HHI takes a wider range of values than the playing time HHI.

We include statistics for three additional variables that will account for team and season varying factors that are correlated with the decisions of coaches in our empirical analysis. We control for variation in team rest with the average number of days between games in a season; this has a sample average of 2.07. The indicator variable "Coach Changed" is equal to 1 if the coach of a team permanently changed at least once during the season; this occurs, according to Table 1, to 13% of teams in our sample. Finally, and most importantly, we control for the competitive environment (i.e. garbage time) with the average absolute value of the point spread of a team in a season. This variable is generated by taking the average of the absolute value of the point spread for every one of team *j*'s games in season *t.* Thus, every team-season combination has a positive average absolute point spread measuring the average amount of garbage time that the team faces. The average of this variable is nearly 11 points, and teams and seasons differ in average point spread by an average of 1 point.

Figure 1 shows histograms for playing-time concentration and talent concentration, our explanatory variables of interest. Since no prior research constructed these measures of the distribution of player inputs, the distributions of these variables represent an important aspect of this analysis.

Both distributions appear relatively symmetric. The talent HHI contains a longer right tail, indicating that a small number of teams in the sample employed a relatively more concentrated distribution of playing time over the course of a season. Neither distribution contains outliers. Both appear to generate substantial variation across team-seasons in the analysis sample.

The relationship between the level of talent on a team and the distribution of talent across seconds of play in games is also of interest, again because no prior research analyzed either of these variables when assessing managerial inputs to win production. Figure 2 plots talent concentration against talent, distinguishing observations by whether the team *j* made the playoffs in year *t*. Note that both variables were normalized to be mean zero and standard deviation one to facilitate comparison. Gold dots identify teams that qualified for the NBA postseason, and blue dots are teams that did not.

Dots to the right of zero on the horizontal axis represents teams with relatively higher player talent inputs to team success and dots to the left of this value represent teams with

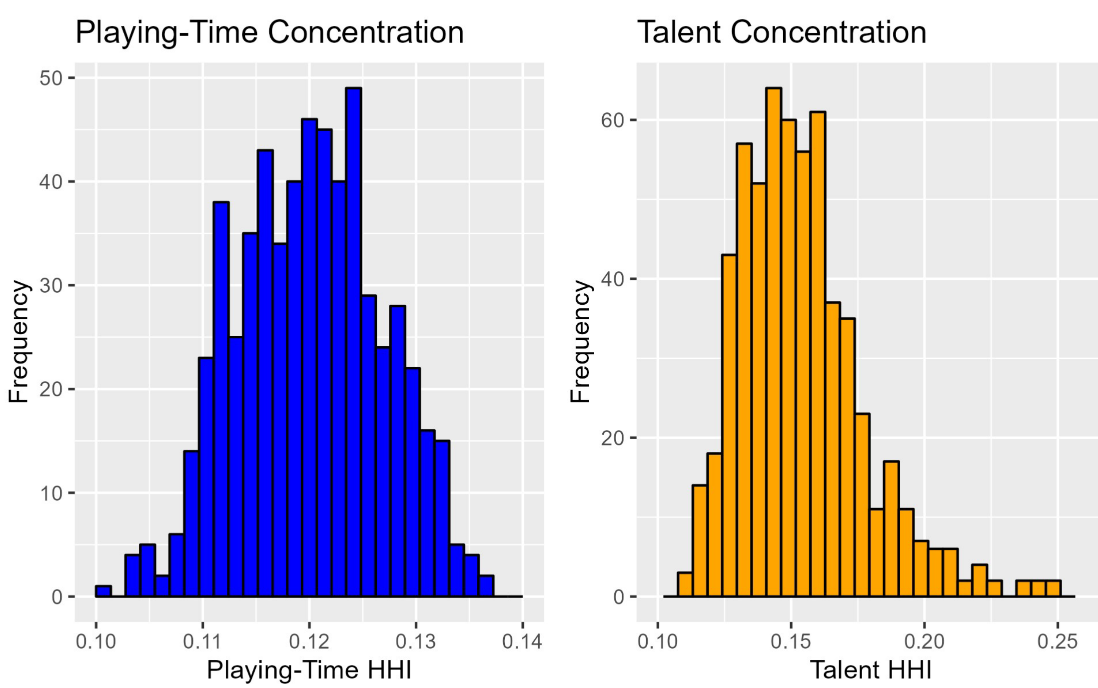

Figure 1: Histograms of HHI Distribution. This figure shows histograms of $sec^{HHI}{}_{jt}$ (left) and $talent^{HHI}{}_{jt}$ (right). Note that talent concentration has a larger range of values compared to playing-time concentration.

lower player talent inputs. Not surprisingly, teams with less overall talent tended to not qualify for the NBA post-season. Gold dots to the left of zero identify overachieving teams and blue dots to the right of zero identify underachieving teams.

Dots above zero on the vertical axis represent teams with managers that employed a relatively more concentrated distribution of playing time in games and dots below this value represent teams with managers that deployed a more equal distribution of playing talent inputs. The relationship between the variables appears to be positive. Managers of teams with more talented players tend to distribute the available playing time less equally than teams with less talented players.

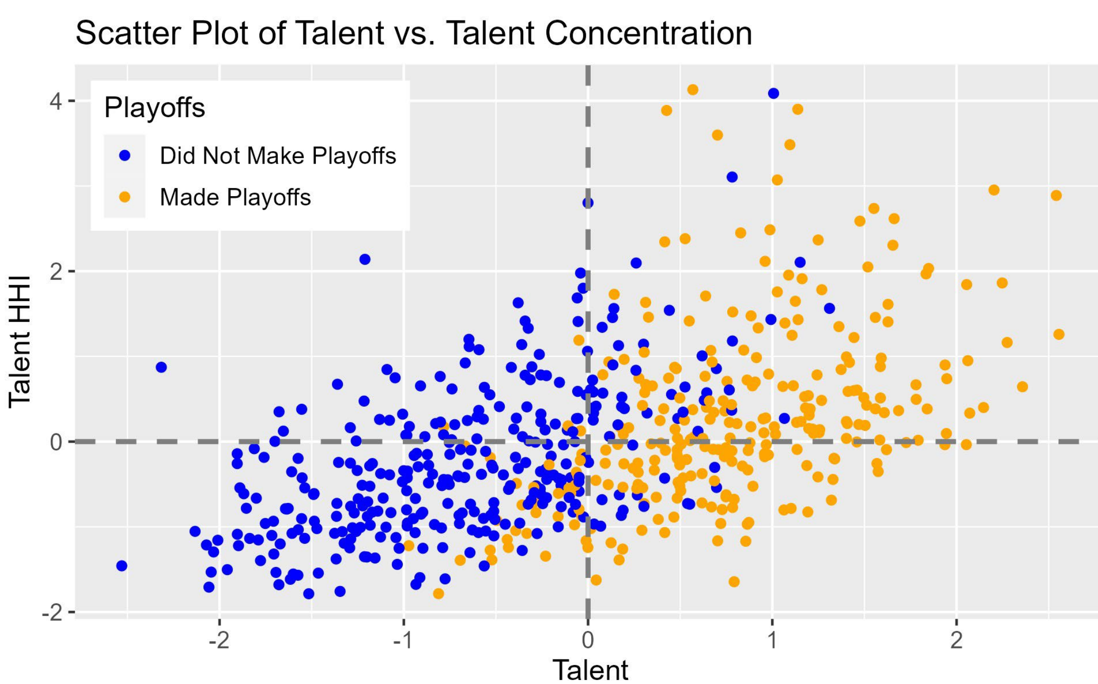

Figure 2: Scatter Plot of Talent vs. Talent Concentration. This figure contains a scatter plot where each point ($talent_{jt}$, $talent_{jt}^{HHI}$) corresponds to a team's average talent and talent HHI for a season. The data are normalized so the means of both variables are 0 and the standard deviations are 1.

Finally, we show that interesting patterns reflecting coach playing time decisions appear in the relationship between player talent and playing time distribution at the individual player level. Figure 3 contains a binned scatter plot of playing time shares s_{igjt} versus player-specific VORP $VORP_{it}$ for all player-game combinations with a positive VORP in the 20 seasons in our sample in which $VORP_{it} \geq 0$. In general, the share of playing time given to players increases with the players' talent as reflected in VORP. Note that the sample mean of player-season specific VORP in the entire sample is 0.78, and its median value is 0.2, meaning Figure 3 visually emphasizes the relationship between high-VORP players and their average share of playing time.

Gold dots on Figure 3 identify players on teams that made the playoffs (successful teams) and blue dots identify players on unsuccessful teams that did not make the playoffs. Consider the gold and blue dots above VORP equal to six on Figure 3. The gold dot, just below 0.10 playing time share, implies that players with a VORP of 6 playing on teams that made the postseason accounted for about 10% of the playing time on their team, on average. The corresponding blue dot is at about 14%, indicating that players with a VORP of 6 playing on teams that did not qualify for the postseason accounted for much more of the playing time on their teams.

One might expect that successful teams play their best players as much as possible and unsuccessful teams do not. Figure 3 shows a quite different outcome in terms of the allocation of playing time. From Figure 3, successful teams allocate less playing time to players of all talent than unsuccessful teams. The Figure shows that the share of playing time for a player of a given VORP is lower for teams that make the playoffs at every VORP value. And successful teams tend to allocate substantially less playing time to their most talented players, those with VORP greater than about 6, than less successful teams.

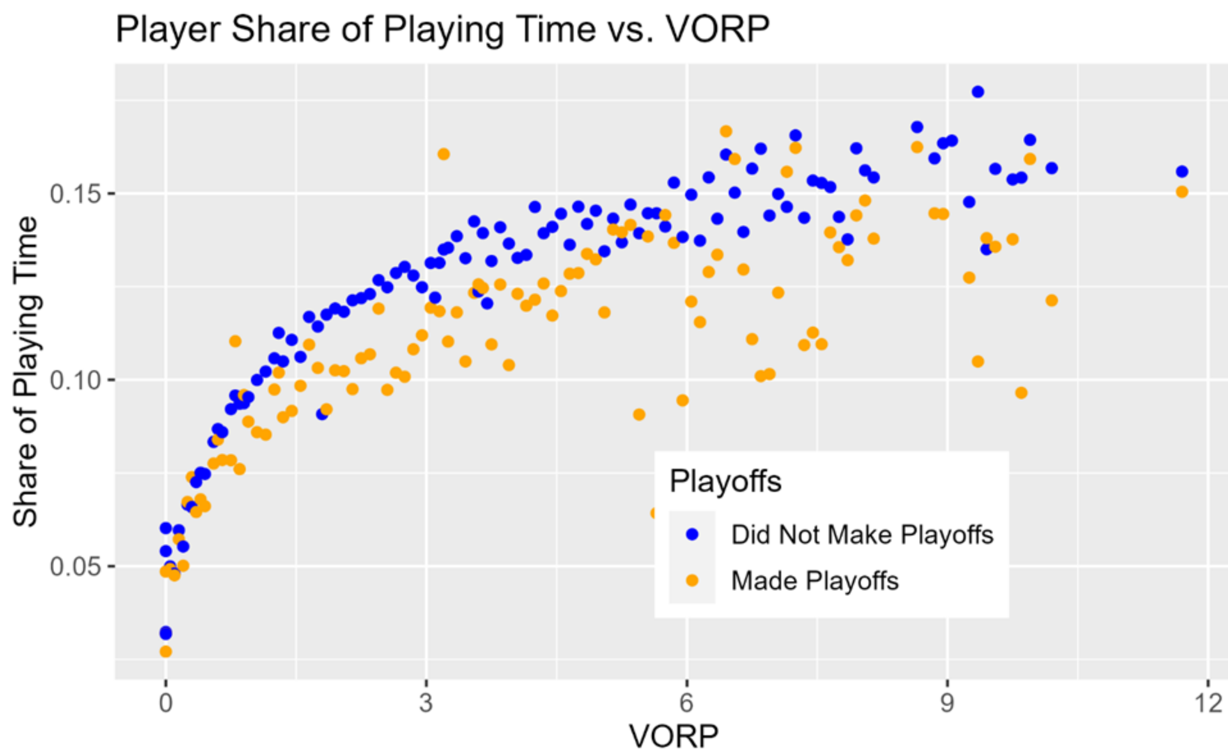

Figure 3: Binned Scatter Plot of Playing Time Share vs. VORP. This figure shows a binned scatter plot of the average share of playing time for specific players with the same VORP.

Empirical Methods

We estimate two-way fixed effects regression models explaining variation in team success, as reflected by regular season winning percentage, using our team-by-season panel analysis data set. Indexing teams by *j* and seasons by *t*, we first estimate a base regression model of the form

$$win\%_{jt} = \alpha_1 talent_{jt} + \alpha_2 talent_{jt}^{Opp} + \alpha_3 daysbtwn_{jt} + \alpha_4 coachchange_{jt} + \alpha_5 sec_{jt}^{HHI} + \alpha_6 talent_{jt}^{HHI} + \gamma_j + \gamma_t + \varepsilon_{jt}$$

where $win\%_{jt}$ is the winning percentage of team *i* in season *t*, $talent_{jt}$ is team *j*'s average level of talent across all games in season *t*, and $talent^{Opp}{}_{jt}$ is the average level of talent used by team *j*'s opponents in season *t*. This variable varies across teams because of the unbalanced NBA schedule and because of variation of opponent's concentration of playing time and player talent across games. These variables reflect player inputs into the production of wins.

The key explanatory variables of interest, variables $sec^{HHI}{}_{jt}$ and $talent^{HHI}{}_{jt}$ are the average levels of team *j*'s playing-time and talent HHIs in season *t*. These variables reflect managers input into the production of team wins. The terms γ_j and γ_t represent team and season fixed effects. Team and season fixed effects capture the impact of unobservable team specific and season specific factors affecting team success.

ε_{jt} is an equation error that captures the impact of all other omitted factors on team win percentage. We assume that this is a mean zero, constant variance random variable. Note that we do not account for the impact of player injuries on win percentage. Under the assumption that player injuries reflect a random process, the equation error term will account for the impact of injuries on game outcomes.

Next, we estimate the following regression model specification in which the effect of playing time and talent concentration is allowed to depend on team talent:

$$
\begin{aligned}
win\%_{jt} = \beta_1 talent_{jt} + \beta_2 talent_{jt}^{Opp} + \beta_3 daysbtwn_{jt} + \beta_4 coachchange_{jt} \\
+ \left(\beta_5^0 + \beta_5^1 talent_{jt}\right) \times sec_{jt}^{HHI} + \left(\beta_6^0 + \beta_6^1 talent_{jt}\right) \times talent_{jt}^{HHI} + \gamma_j + \gamma_t + \varepsilon_{jt}
\end{aligned}
$$

The regression above is a fixed-effects regression with an interactions of $talent_{jt}$ and each of $sec^{HHI}{}_{jt}$ and $talent^{HHI}{}_{jt}$. The equation is algebraically arranged to emphasize that the effect of playing-time and talent concentration on winning percentage are linear functions of the team's talent. We include the interaction of talent and talent concentration in our specification to account for varying *strategic* incentives that are unobserved in data. The impact of manager decisions on the allocation of playing time could vary systematically with the player talent on the team.

The notation of regression coefficients across model specifications reflects association with specific independent variables. For example, the effect of playing-time concentration $sec^{HHI}{}_{jt}$ on win percentage $win\%_{jt}$ is α_5 and $\beta_5^0 + \beta_5^1 talent_{jt}$ in the base and interacted models, respectively. The parametersα_7, β_6^0, and β_6^1similarly define the effect of talent concentration,

$talent_{jt}^{HHI}$.

Note that results from these regression models reflect the association between managerial decisions and team success, not a causal relationship. This setting clearly contains unobserved time varying team level factors that affect team success in a season and are also correlated with playing time decisions, for example the number of blowout games a team plays in over a season. Documenting association between a manager's allocation of playing time across a season and team success represents a contribution since no prior research focused on the allocation of playing time. Future research will address the issue of causality.

Results

Table 2 contains the results of estimating Equations 12 and 13 using different sets of explanatory variables. All explanatory variables are standardized to mean zero and standard deviation one, so parameter estimates reflect the impact of a one standard deviation change in each variable.[4] Every specification in Table 2 includes season and team fixed-effects, and standard errors are clustered by season. Model 1 represents the baseline model specification in which only the player inputs of team *j* and its opponents are used as explanatory variables. Note that after controlling for playing-time and talent concentration in Models 2, 3, and 4, the explanatory power of the regression models (as measured by root-mean-squared-error, RMSE) improves.

Results from Model 1 show that the VORP-based player talent input variables affect team success in the predicted way. Teams employing more player talent win more games. We measure winning percentage using a variable with a 0 to 100 scale, where one additional win in an 82 game season increases winning percentage by 1.2. The parameter estimate on the talent variable, 14.1, implies that a one standard deviation increase in playing talent inputs increases team wins by about 12 over the course of a season.

While the point estimate on the opponent playing talent variable is negative, the estimated standard error is large and the parameter estimate is not statistically different from zero. This probably reflects the lack of variation in the opponent team talent variable. The average number of days between games in a season has no impact on team success. Teams that change coaches mid-season lose about one more game on average than teams that do not change coaches.

Models 2 and 3 add the playing time and talent HHI variables, reflecting manager decisions, separately. The parameter estimates on both variables are statistically different from zero. Manager decisions about the allocation of playing time in games are associated with significant changes in team winning percentage, holding player inputs constant. Manager decisions about the allocation of playing time matter. The parameter estimates are both negative. Teams managed by coaches who decide to concentrate playing time among fewer players over the course of a season lose more games. Teams managed by coaches who decide to spread playing time more evenly across players over the course of a season, reducing the HHI, win more games.

[4] Specifically, $daysbtwn_{jt}$, $coachchange_{jt}$, and $\mathrm{absspread}_{\mathrm{jt}}$ are not normalized, while each of $talent_{jt}$, $talent^{Opp}_{jt}$, sec^{HHI}_{jt}, and $talent^{HHI}_{jt}$ are.

The size of the parameter estimates on the playing time and talent HHIs indicate that a one standard deviation decrease in the concentration of playing-time across players, a more equal distribution, leads to about one additional win per season. A one standard deviation decrease in the concentration of talent leads to about two additional wins per season, a larger impact. The allocation of playing talent is associated with a larger increase in team success than the allocation of playing time.

Model 4 includes both HHIs in the same regression model. Managers' decisions about the allocation of playing time and playing talent both matter, in that they are both associated with significant changes in team winning percentage. Again, the impact of the distribution of playing talent is larger than the distribution of playing time, but both imply that more evenly distributed playing time and talent are associated with increased team success.

The results in Model 4 establish a robust association between coach decisions about the allocation of playing time across players and team performance. The variable sec^{HHI}_{jt} reflects only coach choices, and it remains significant when we include the closely related $talent^{HHI}_{jt}$ variable, which has a small component of variation driven by non-coach decisions regarding playing time because it depends on VORP. Ultimately, this means the underlying team win production function that translates game-team level competitive inputs $talent_{gjt}$ and $talent^{Opp}_{gjt}$ into wins and losses also includes some structural component reflecting both talent and playing-time concentration.

Table 3 contains results from the interacted model specification shown in Equation 13. Model 1 interacts playing-time HHI with player talent inputs, Model 2 interacts talent HHI with talent, and Model 3 contains both interaction terms. These results show playing-time concentration sec^{HHI}_{jt} and talent concentration $talent^{HHI}_{jt}$ independently and jointly explain significantly more variation in team success. Furthermore, they show that the relationship between concentration and win percentage depends on the overall level of player talent on the team, where the effect of concentration in both playing time and talent is negative and decreasing in the level of team talent.

To better interpret these regression results, we plot the effect size of playing time and talent concentration as a function of talent. Figure 3 shows these estimates. The horizontal axis on 3 shows the level of player talent inputs in one standard deviation units. The vertical axis shows changes in winning percentage in percentage points. Each line shows the impact of a one standard deviation change in the HHIs.

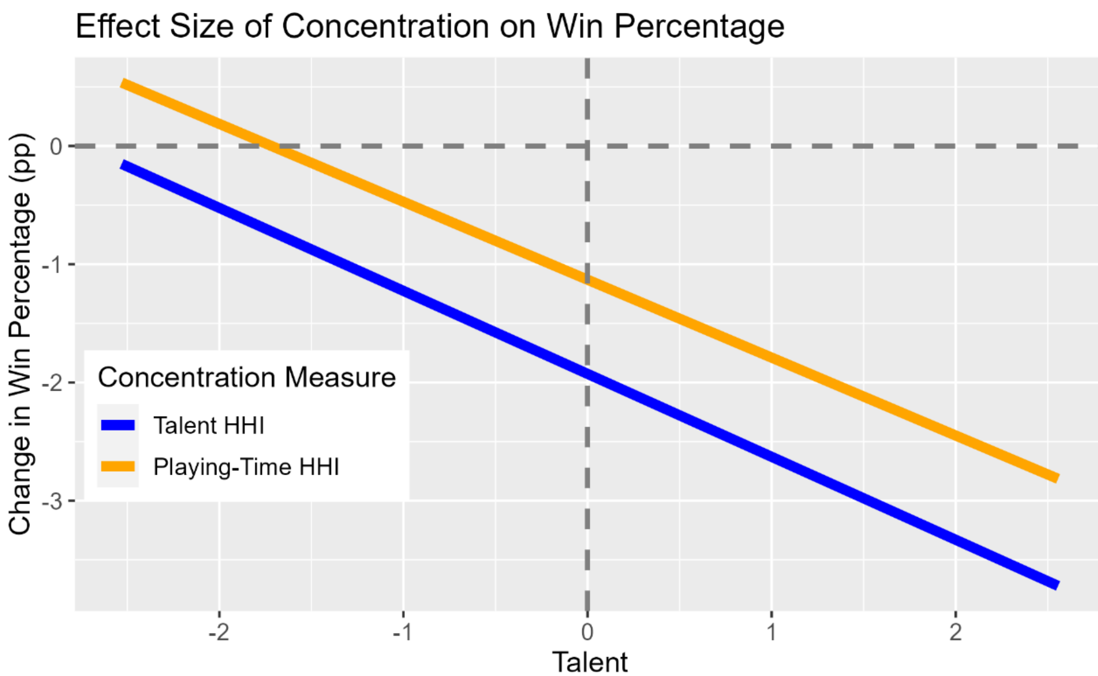

Figure 4: Marginal Effect of Concentration. This figure displays the predicted change in win percentage from a 1 standard deviation increase in Playing-Time HHI (blue) or Talent HHI (orange) based on estimates from the full interaction model in Equation 13, Model 3 on Table 3. Estimates are normalized so that a level of team talent of 0 corresponds to the average level of talent on NBA teams in the sample, and a talent level of *e* corresponds to an *e*-unit SD increase in player talent inputs from the mean. The lines reflect the impact of one standard deviation changes in the HHIs.

From Figure 4, consider the impact of a one standard deviation decrease in talent HHI on team success on a team with playing talent one standard deviation above the league average. Reading up from 1 on the horizontal axis to the blue line, this coach-driven change in the allocation of playing time leads to about a 2.5 percentage point increase in season winning percentage, a change of about 2 wins per season. On a team with talent one standard deviation below the league average, a one standard deviation decrease in the concentration of talent is associated with a change in winning percentage of slightly less than 1.5, approximately one more win over the course of a season. The impact of the playing-time HHI is smaller, but the impact of a more equal distribution of talent on team success is still positive for all teams except those with well below average player talent.

Table 4 contains the results from alternative models that use a different set of variables to identify teams that play in a large number of blowout games with large final point differentials over the course of a season. As discussed above, systematic differences in the number of blowout games teams play in over the course of a season could bias the parameter estimates of interest up overstating the role played by incentives to win games over the course of a season in driving playing time decisions. To address this, we use alternative variables based on point spreads and game outcomes in games played in each season. We also include an alternative measure of the talent on teams, the arithmetic difference between talent on the two teams and the absolute value of this difference.

Model 1 on Tale 4 simply repeats the results from Model 4 in Table 2. Models 2 through 7 add alternative variables reflecting the presence of blowout games on a team's schedule over the course of the season, including point spreads greater than 20 points. We also use the betting market money line to estimate implied win probabilities and include the number of games played over the course of the season that have implied win probabilities of greater than the 75th percentile and less than the 25th percentile. These variables will reflect the number of blowout games teams play in.[5]

The key results on Table 4 show that the parameters of interest, on the playing time concentration variables, do not change when any of these variables are added to the models. Our results appear robust to controlling for the number of blowout wins or losses teams appeared in. The parameter estimate on the arithmetic difference in talent for the two teams is positive, statistically significant, and close to the value of the parameter on the talent variable in the other six models on Table 4.

Conclusions

We develop evidence of a positive association between manager decisions about the allocation of valuable, rare, and imperfectly imitable team resources and team production of wins, a core product of sports teams. The more equally distributed playing time across the team roster over the course of a season, the more games an NBA team wins. These results extend the literature analyzing the role played by team coaches on sports team success by identifying a potential mechanism through which coaches impact game outcomes. This association provides empirical researchers with a new variable to use when empirically analyzing the production of wins that can be easily calculated in other settings.

The results have some limitations. The relationship between concentration measures and team success reflect associations, not a causal impact. The headline result of a positive association between more equal playing time and team success holds on average over the entire NBA season and over all coaches. The results from the models interacting team talent and the concentration of playing time suggest heterogeneity in the relationship which likely exists across head coaches. The results do not account for the role played by injuries in the allocation of playing time across a team roster. Future

[5] Win probabilities are computed from money line (American) odds using the standard normalization.

research should investigate the causal nature of the relationship between team success and playing time distribution. Game-level data would provide a good setting for this type of analysis.

Several possible extensions of this research can address these limitations. Applying concentration measures at the game level would permit an analysis of the impact of these manager decisions on individual game outcomes. A game level analysis would facilitate the implementation of causal inference methods like the exploitation of team elimination from playoff contention like in Gong et al. (2022) or an instrumental variables approach like in Kordyaka et al. (2022). Game level data would also facilitate estimating empirical models that interact coach fixed effects with playing-time and talent HHI to identify coaches who make highly effective decisions about the allocation of playing time. Game level data would also make it possible to control for the impact of factors affecting the allocation of in-game playing time outside the control of the manager, like the number of fouls called in a game and the impact of time between games on decisions about the utilization of team resources.

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	Model 1	Model 2	Model 3	Model 4
Average of Talent (across games of a Team in a Season)	14.116***	14.355***	15.355***	15.373***
	(0.253)	(0.239)	(0.280)	(0.277)
Average of Opponent Talent	-0.911	-0.673	-0.630	-0.512
	(0.693)	(0.673)	(0.669)	(0.663)
Average # of Days between Games	10.632	18.112	21.662	25.139
	(24.618)	(24.261)	(23.100)	(23.159)
Coach Changed in the Season	-1.427**	-1.235*	-0.649	-0.612
	(0.670)	(0.644)	(0.632)	(0.630)
Average Playing Time Concentration		-1.487***		-0.922***
		(0.305)		(0.266)
Average Talent Concentration			-2.366***	-2.117***
			(0.343)	(0.323)
Observations	595	595	595	595
RMSE	4.54	4.44	4.27	4.23
Std.Error clusters	by: team	by: team	by: team	by: team

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 2: Base Model Results. This table contains results from estimating the regression model in Equation (12), where the dependent variable is Win Percentage, $win\%_{jt}$. All independent variables are normalized to mean 0 and standard deviation 1. Standard errors are clustered at the season level and all model specifications include team and season fixed effects.

	Model 1	Model 2	Model 3
Average of Talent (across games of a Team in a Season)	14.307***	15.195***	15.252***
	(0.223)	(0.278)	(0.275)
Average of Opponent Talent	-0.693	-0.940	-0.749
	(0.677)	(0.711)	(0.696)
Average # of Days between Games	22.954	23.641	31.627
	(24.293)	(22.851)	(23.126)
Coach Changed in the Season	-1.533**	-0.884	-1.002*
	(0.606)	(0.617)	(0.585)
Average Playing Time Concentration	-1.518***		-1.131***
	(0.280)		(0.226)
Average Talent times Average Playing Time Concentration	-0.847***		-0.659***
	(0.203)		(0.218)
Average Talent Concentration		-2.092***	-1.927***
		(0.376)	(0.390)
Average Talent times Average Talent Concentration		-0.854***	-0.702**
		(0.273)	(0.308)
Observations	595	595	595
RMSE	4.37	4.21	4.11
Std.Error clusters	by: team	by: team	by: team

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 3: Interacted Model Results. This table contains results from estimating the regression model in Equation 13, where the dependent variable is Win Percentage, $win\%_{jt}$. All independent variables are normalized to mean 0 and standard deviation 1. Standard errors are clustered at the season level and all model specifications include team and season fixed effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Average of Talent (across games of a Team in a Season)	15.373***		15.304***	15.351***	15.281***	8.122***	8.763***
	(0.277)		(0.279)	(0.274)	(0.446)	(0.595)	(0.691)
Average of Opponent Talent	-0.512		-1.341*	-0.807	-0.808	-0.407	-1.144*
	(0.663)		(0.732)	(0.683)	(0.681)	(0.533)	(0.585)
Average # of Days between Games	25.139	28.936	25.604	26.709	26.972	-8.888	-8.265
	(23.159)	(22.626)	(21.389)	(22.822)	(22.825)	(24.870)	(23.065)
Coach Changed in the Season	-0.612	-0.773	-0.581	-0.534	-0.544	-1.725**	-1.620**
	(0.630)	(0.667)	(0.599)	(0.647)	(0.641)	(0.695)	(0.726)
Average Playing Time Concentration	-0.922***	-0.834***	-1.116***	-0.982***	-0.979***	-0.714**	-1.113***
	(0.266)	(0.283)	(0.270)	(0.263)	(0.264)	(0.265)	(0.260)
Average Talent Concentration	-2.117***	-1.999***	-2.077***	-2.120***	-2.100***	-1.395***	-1.426***
	(0.323)	(0.350)	(0.315)	(0.321)	(0.313)	(0.350)	(0.342)
Average of Talent-Opponent Talent		14.874***					
		(0.289)					
Average of |Talent-Opponent Talent|			-1.029***				
			(0.245)				
Percent of Games with |Points - Opponent Points| >= 20				-0.072*			
				(0.038)			
Percent of Games with Points - Opponent Points >= 20					-0.064		
					(0.066)		
Percent of Games with Points - Opponent Points <= -20					-0.080		
					(0.056)		
Average Money-Line implied win probability						58.351***	
						(5.057)	
Number of Games with win probability below 25%							-0.318***
							(0.044)
Number of Games with win probability above 75%							0.131***
							(0.033)
Observations	595	595	595	595	595	358	358
RMSE	4.23	4.32	4.14	4.22	4.22	3.27	3.33

Models 6 and 7 (with win probability) are for seasons 08/09 to 18/19, only. All other specifications are for seasons 99/00 to 18/19.

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4: Estimates of the base model with alternative measures of blowout games. Note that Model 4 in Table 2 is the same as Model 1 in Table 4. We define alternative blowout game indicators as the number of games with an absolute point spread larger than 20 and with indicator variables for having absolute point spread between 10 and 12 and for over 12, with the reference group being an average absolute point spread less than 10. Models 2 to 7 show that including these measures, causes negligible changes in the estimated parameters of interest on the playing time concentration variables.