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ORIGINAL ARTICLE

Economic Inquiry

The importance of high performing team members in complex team work: Results from quasi-experiments in professional team sports

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Abstract

This paper empirically assesses peer effects of high performing team members in reciprocally interdependent team production. Using data from the National Basketball Association (NBA), we identify peer effects by exploiting unforeseen in-game injuries of high performing players. Results indicate that without a high performing player, other team members maintain efficiency and the division of tasks among each other. However, they slightly increase risk taking and decrease their individual output, resulting in an inferior overall outcome. These effects depend on whether a high performing player has a team-oriented or a self-oriented role in the team. Additionally, we observe that relatively skilled players try to step in for the absent high performing player.

KEYWORDS

high performing workers, interdependent production, peer effects, quasi-experiment, team production

JEL CLASSIFICATION

J24, L23, L83

1 | INTRODUCTION

In modern economies, many tasks are executed by appointed teams of workers. Thereby, output is a function of the combined effort of multiple team members (Alchian & Demsetz, 1972; Mas & Moretti, 2009). Some arbitrary examples include police intervention, R&D, software development, surgery, political campaigns, construction, engineering, product development, consulting, and professional sport teams. One salient characteristic of team production is peer effects, that is, genuine effects on worker's productivity which result from the circumstance of having co-workers (Ichniowski & Preston, 2014). Peer effects are essential for many organizations because “mechanisms in which

Abbreviations: DiD, Difference-in-Difference; DiDiD, Difference-in-Difference-in-Difference; FGA, Field Goal Attempt; FG %, Field Goal Percentage; FT, Free Throw; HPTM, High Performing Team Member; NBA, National Basketball Association; OLS, Ordinary Least Squares; PER, Player Efficiency Rating; WP, Wins Produced.

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individuals influence the productivity of others … directly influence the performance of organizations …" (Oettl, 2012, p. 1138).

In this context, high performing team members (HPTM) are of particular interest. Besides a large individual contribution to team performance, they may disproportionally affect other team member's performance. Peer effects of HPTMs can be positive or negative. Positive peer effects occur when team members are either positively motivated by the HPTM's performance or the HPTM directly facilitates task fulfillment. In this regard, Oettl (2012) emphasizes the social dimension of "helpfulness" to other team members. In the case of negative peer effects, a serious effort by a HPTM can induce other team members to take a free ride or a particularly dominant HPTM reduces opportunities of the other team members to perform well.

The literature on peer effects often proposes behavioral explanations, such as mutual monitoring and peer pressure, social norms, shame, reputation, or guilt (Cornelissen et al., 2017; Georganas et al., 2015; Kandel & Lazear, 1992; Mas & Moretti, 2009; Simester & Knez, 2000). These concepts strongly rely on the degree of observability (and measurability) of individual performance by peers or a principal (Ichniowski & Preston, 2014; Mas & Moretti, 2009). For instance, if it is difficult to attribute team performance to individual team members, motivation loss and social loafing can appear in the presence of a HPTM, which corresponds to a negative peer effect (Irwin & Feltz, 2016; Osborn et al., 2012). Apart from behavioral concepts, Gould and Winter (2009) propose an approach that fully relies on rational considerations, that is, income maximization, when only overall team performance is observable. A team member's effort then lowers (increases) the effort of peers if they are substitutes (complements) in the production process.

Although it is widely acknowledged that peer effects matter empirically (Ichniowski & Preston, 2014), evidence for the effect direction is mixed. In an extensive systematic review of studies on peer effects, Herbst and Mas (2015) report that 60% of the reviewed papers find significant, mostly positive peer effects, while 40% find no evidence. Most of these studies examine how relatively more productive individuals affect their peers' performance. Similar to the present research, however, in a different work environment Azoulay et al. (2010), Oettl (2012), and Waldinger (2012) explicitly focus on the subgroup of HPTMs. Specifically, they find positive and significant peer effects in coauthoring scientific papers with HPTMs. Another feature that many of the studies reviewed by Herbst and Mas (2015) have in common is no or only little interdependence between peers.[1] Similarly, research on peer effects in team production predominantly examines settings with little direct interaction among team members or with a strictly sequential workflow. A prominent example is the study of Mas and Moretti (2009) that finds strong positive productivity effects of relatively more productive supermarket cashiers on other cashiers in the same shift. They conclude that positive peer effects dominate free-riding behavior when cashiers are within visual sight of each other but only in limited indirect productive interaction, that is, substituting each other in the final output production.

To date, much less attention has been paid to peer effects in complex team production processes prevailing in many real world workplaces. Complex team production can be characterized by close, constant and often ad hoc interaction among multiple team members. Thompson (1967, p. 55) calls this situation "reciprocal interdependence", where "the outputs of each become inputs for the others". In the present empirical study, we want to fill this gap by examining peer effects when production is reciprocally interdependent. Our focus is exclusively on peer effects of HPTMs.

We address two prominent difficulties of empirical studies on team production. First, there is often a lack of observability and missing or incomplete performance data (Arcidiacono et al., 2017; Kuehn, 2017; Mas & Moretti, 2009). Second, it is challenging to find a setting which allows for causally isolating peer effects. To overcome these caveats, we use professional sports as real world laboratory. In professional sports, team production is common and diverse, including many reciprocally interdependent activities. Moreover, sports data allow precise identification and measurement of individual and team performance. Further, data are abundant and individual characteristics are detailed and complete (Arcidiacono et al., 2017; Kahn, 2000; Kendall, 2003; Neugart & Richiardi, 2013). Finally, sport environments provide the opportunity to exploit quasi-experiments (Kahn, 2000; Neugart & Richiardi, 2013).

Specifically, we use data from professional basketball, namely, the National Basketball Association (NBA). The structures of professional basketball are often considered a suitable comparison to many corporations (Chen & Garg, 2018; Day et al., 2012; Keidel, 1985). Production in basketball is reciprocally interdependent and entails complex interactions among team members with different skill levels (Chen & Garg, 2018; Ishak & Ballard, 2012). Basketball players take on different roles (e.g., positions on the court) but at the same time are required to possess a great deal of generalist skills (Keidel, 1985). Finally, similar to many other tasks in modern economies, there is substantial competition and time pressure during a basketball game.

Previous empirical research on peer effects in sports examined sequential interactions among team members, for example, in athletics relay teams (Depken & Haglund, 2011), in swimming relay teams (Neugart & Richiardi, 2013), and in baseball (Gould & Winter, 2009). We are not aware of empirical studies on peer effects in reciprocally interdependent production, such as basketball. Existing papers that partially relate to peer effects in basketball do not explicitly address HPTMs and have different foci. For example, they measure the individual contribution of basketball players to overall team success depending on the peers with whom they are playing (Arcidiacono et al., 2017; Kendall, 2003; Kuehn, 2017).

To answer our research question, we exploit unexpected, sudden injury dropouts of high performing players during NBA games. Adaptation to the changed environment of team members who are still in action (hereinafter remaining team members) must occur immediately and is based on preexisting resources. The sole focus on within-game changes in performance is restrictive in that it allows little scope for tactical adaptation or practicing. It allows, however, to isolate the direct effect on performance when an important team member is missing during a given team task or project. Hence, it conversely allows to draw conclusions on the peer effects which stem from the team member if the respective member is present. Injury dropouts of important team members in team sports and the effect on peers have been studied previously (e.g., Chen & Garg, 2018; Stuart, 2017). In the respective contexts, the remaining team members did have time to adapt at least until the subsequent game, for example, by reassessing the organization of human capital or practicing. Hence, the causal identification strategy is less clear-cut and prone to potential confounders which might be associated with the adaption process taking place between games.

We operationalize team members' performance with four measures: Field Goal Percentage (FG %), a measure for efficiency; expected individual FG %, a measure for risk taking; the number of Field Goal Attempts (FGA), a measure for output; and the distribution of FGA among team members. To these four measures, we add the number of points scored as team outcome variable. All performance measures relate to offense production, that is, scoring. Offense production can be clearly separated from defense production. And compared to defense production, performance measurement in offense production is based on comprehensive, valid, and observable indicators. Applying a difference-in-difference (DiD) approach, we show that the injury dropout of a HPTM does not change efficiency nor the distribution of tasks among team members. However, remaining team members take more risk and reduce output. Overall, the team scores fewer points. The effects are partially smaller for teams with higher average skills. In addition, the effects are driven by HPTMs with a team-oriented rather than a self-oriented role in the team. Eventually, remaining HPTM (other than the HPTM who drops out) react differently to the dropout than the average team member. They seem to step in (or take advantage of the window of opportunity) by increasing output, however, without managing to fully compensate. Based on our results, we argue that with constant and reciprocal interaction, the facilitating nature of (some) HPTMs potentially is the most important mechanism for the observed peer effects.

We extend previous findings on peer effects from less interdependent and sequential settings by showing empirically that peer effects of HPTMs exist in reciprocally interdependent team production in real world contexts. Our results reveal how team members react immediately to an unexpected absence of a HPTM, that is, without having much opportunity to adapt. Moreover, our study allows a disaggregated view on peer effects by considering the roles of HPTMs and the moderating influence of the average skill levels in a team.

The remainder of this paper is organized as follows: Section 2 describes the empirical setting, the identification strategy, and the data, while Section 3 introduces the model and the variables. We present our results in Section 4, together with comments on robustness. Section 5 discusses the results in a broader context and concludes the paper.

2 | EMPIRICAL SETTING AND DATA

We obtain play-by-play data of $N = 6{,}423{,}839$ events in 15,707 NBA games, spanning 13 regular seasons from 2004/05 to 2016/17, from ESPN, the major US based sports television channel. Play-by-play data include a complete sequence of outcome-relevant events during a game, such as FGA, free throws (FT), rebounds, turnovers, fouls, ejections, substitutions, and timeouts. We exclusively focus on FGA taken by a given team during a game ($n = 1{,}286{,}180$ FGA). We complement play-by-play data with important player characteristics (e.g., performance, position, injuries) and team characteristics (e.g., team performance) from https://www.prosportstransactions.com (injuries), http://insider.espn.com/nba:hollinger/statistics, https://sites.google.com/site/rodswebpages/codes (player statistics), http://stats.nba.com (player and team statistics), and https://www.espn.com (injuries).

To identify high performing players in the NBA, we use Wins Produced (WP), a measure that indicates how many team wins a player contributes in a given season. It thereby objectively measures a player's marginal product. WP is calculated based on a variety of individual performance statistics (Berri, 2018; Berri & Krautmann, 2006; Berri &

Schmidt, 2010).[2] We identify players as high performing if their WP belongs in the top 20% percentile of the distribution of WP of all NBA players in a given season. Other definitions of high performing peers are plausible, for example, one could solely focus on the highest performing peer (resulting in a significantly smaller sample) or a smaller percentile (i.e., results of this paper remain unchanged if HPTM are identified as belonging to the top 15% percentile in terms of WP). However, using the top 20% percentile is justified by the "80-20" rule echoed by practitioners, stating that 80% of the work in a firm is accomplished by 20% of the workers (Chen & Garg, 2018). We include only high performing players who play at least half of all games in the given season and on average are at least half the total game time on the court during these games. This method avoids considering high performing players with small influence on other team members due to little presence.

To isolate the contribution of high performing players on their peers, we exploit unforeseeable injury dropouts during a game. Injuries create a quasi-experiment "[s]ince injuries are unpredictable and beyond anyone's control […]" (Chen & Garg, 2018, p. 1250). Injuries usually happen as a result of an unforeseen event and are independent of coaching decisions or individual performance. We then examine performance of peers of the high performing player before and after the injury dropout. The context (the game) thus stays the same, which is important since in the heat of the moment, there is only limited opportunity to adapt to the changed situation. For instance, the roster for that particular game is fixed and no new plays or routines can be developed and practiced. Figure 1 visualizes our identification strategy.

While the "NBA Injury Report" includes players who miss entire games because of an injury, there is no data for in-game injuries. To identify relevant games, we follow a multi-stage procedure. First, we pick all games with missing high performing players due to an injury. Second, we look at the last game before the high performing player appears on the injury report. We assume an in-game injury if a high performing player definitively leaves this game before the end of the third quarter. In addition, we require that the high performing player's court time during this game is between 40% and 75% of his season average. The lower bound[3] ensures a certain influence of the player on the other team members, while the upper bound considers the early leave due to the injury. Third, we draw a random sample of 100 identified games and cross-check with ESPN media reports if there is an injury dropout of the high performing player, which we can confirm in all 100 cases. The resulting sample consists of FGA taken by members of teams whose high performing player drops out due to an injury ("injury dropout group"). Even though this procedure proves to be effective to identify the respective games it is limited to HPTM only and, therefore, restrictive in some ways. In theory, non-HPTM, that is, other players of the team could also form the focus of investigation, however, our approach is not suitable in these cases for the following reasons. First, non-HPTM have significantly less court time and it is not uncommon for them to leave the court before the end of the game. Accordingly, it is more difficult to detect an unexpected dropout of these players from the data. Second, media reports are less likely to report on injuries of non-HPTM.

We add a control group to cope with other factors that affect performance in the course of a game and cannot (completely) be controlled for (e.g., game progression). The control group consists of FGA taken by members of a randomly chosen team whose high performing player (according to the criteria described before) does not drop out and

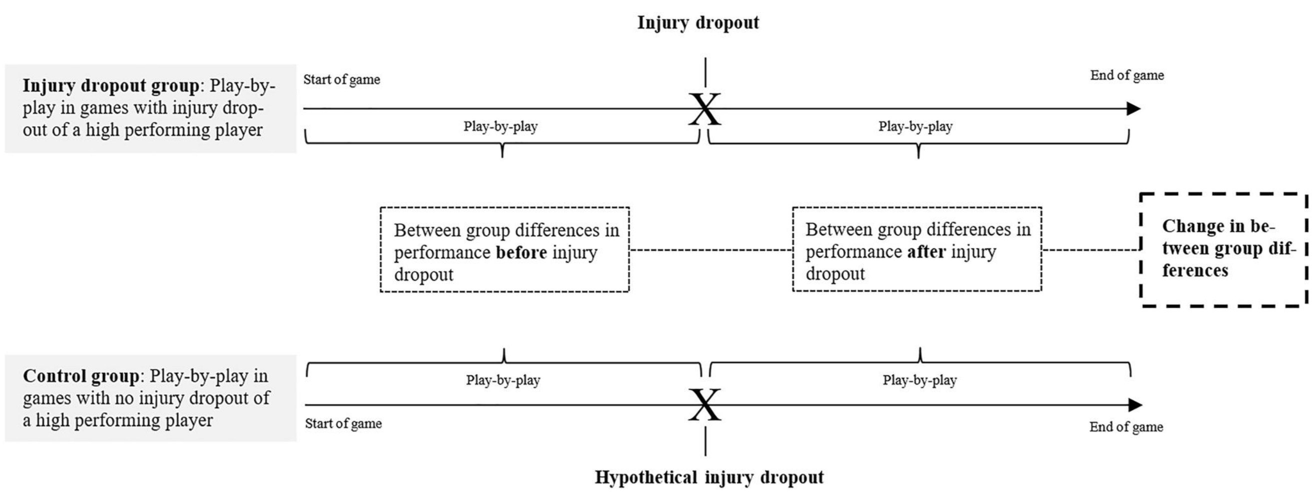

FIGURE 1 Identification strategy

is on court at least 90% of his season average. In the control group, we divide the before and after period using the average remaining game time after the injury dropouts in the injury dropout group.

Defining an injury dropout group and a control group allows the use of a difference-in-difference (DiD) estimation strategy (Angrist & Pischke, 2008). We compare the change in performance before and after the injury dropout between the two groups.

To achieve an optimal empirical setting and causal identification strategy, games within the sample should be sufficiently similar with the exception of the injury dropout. Hence, several exclusion restrictions are applied to yield the final sample. We exclude $n = 965{,}960$ FGA in 11,780 games in the following instances: any high performing player drops out due to a different reason than injury (e.g., ejection; $n = 131{,}236$ FGA in 1588 games); more than one high performing player drops out due to any reason ($n = 991$ FGA in 12 games); and at least one high performing player does not play (e.g., due to rest, prior injury, or personal reasons) or does not fulfill the requirements stated above (e.g., minimal amount of games played in a season or minimal court time during a given game). The latter instances sum up to $n = 833{,}734$ FGA in 10,180 games.

Last, we restrict the period before and after the dropout to 12 min to ensure comparability. We thereby exclude another $n = 164{,}090$ FGA. In total, our sample consists of $n = 12{,}262$ FGA in 308 games (injury dropout group) and $n = 143{,}869$ FGA in 3619 games (control group). To increase the sample size and check for robustness we relax these restricting assumptions in various ways, for example, by including high performing players with less than the minimal amount of games played in a season, the minimal court time during a game, and the minimal average court time during a season. Results are robust against these relaxations.

3 | MODEL

3.1 | Variables

The dependent and independent variables are briefly summarized in Table 1 and described below.

Five performance measures serve as dependent variables. The first performance measure is FG %, reflecting the ratio of a player's successful FGA to his total FGA. It is a measure for a player's shooting efficiency that mainly depends on a player's skills and the zone of the basketball court the FGA is taken from (Figure 2). Because we control for how well a player on average scores from a given zone of the court, we do not expect an effect of the high performing player's injury dropout on the efficiency of other players.

The second performance measure is expected individual FG %, a measure for risk taking. It reflects how promising a player's shooting position is in terms of a successful FGA. We calculate this variable using the career FG % of a player making an attempt from a particular zone of the basketball court (Figure 2). We hypothesize that high performing players create opportunities for other team members, bringing them into promising positions for FGA and thereby increase their expected individual FG % (which corresponds to lower risk). We expect risk to increase after an injury dropout of a high performing player.

The third performance measure is the number of FGA normalized to 48 min, a measure for output. High performing players may speed up the pace of the game, thereby increasing output of all team members. Hence, we expect output to decline after an injury dropout of a high performing player. Results report output as a team variable including the injured high performing player. There are two reasons for this: First, the interpretation is more straightforward and directly linked to the outcome variable (points scored). Second, ignoring the high performing player requires to estimate the court time of all other players for the 12 min before and after the dropout event. While the data in principal allows for this estimation, it comes with some inaccuracy (e.g., due to outliers). However, results are robust against the different specifications.[4]

The fourth performance measure is task allocation, measuring team routines. We use shot balance as a proxy for this variable.[5] Shot balance measures the distribution of FGA among players while taking into account the players' court times. A higher shot balance indicates a more equal distribution of FGA among players. Since high performing players supposedly are dominant players, we expect a more equal distribution of FGA after the injury dropout.

The fifth performance measure is the number of points scored normalized to 48 min, a measure of team outcome in offense production. Based on our expectations for the previous four measures, we expect that team outcome declines after the injury dropout. The first three measures exclude the high performing player from the analysis, that is, the results present how the remaining team members adapt to the injury dropout.

TABLE 1 Variable overview

Variable	Description	Reason for inclusion as dependent variable
Dependent variables		
FG %	Field Goal Percentage (FG %) measures the successful percentage of shot attempts from the field. It depends on the ability of a player, the court zone where a shot is taken, and the competing team's defense behavior. A higher FG % indicates higher efficiency	FG % is a measure for efficiency.
EXPECTED INDIVIDUAL FG %	Expected Field Goal Percentage for every FGA in %. Every FGA has a success probability that depends on zone specific (Figure 2) career FG % of the player taking the FGA. A higher average FG % corresponds to a lower risk	Average FG % is a proxy for how risky FGA are on average. It is also used as control variable
FGA 48	Number of Field Goal Attempts (FGA) normalized to 48 min. A higher FGA per 48 min indicates a higher pace in output production and thus more output	FGA 48 is a measure for output
SHOT BALANCE	Shot balance measures how (un)evenly FGA are distributed among players of a team, controlling for differences in court time of players. A low shot balance indicates a skewed distribution, that is, a higher concentration of FGA with few(er) players	Shot balance measures the distribution of FGA among players
PROPORTION OF 3S	The proportion of three point FGA on total FGA in %	This measure is a (rough) indicator for risk taking
SCORE 48	Number of points scored normalized to 48 min. A higher value indicates a better outcome	Score 48 is the most relevant outcome variable for offense production
Independent variables		
TEAM WP	Average WP of all players on court in a given game, weighted by court time of the players	WP is used as a measure for a team's average ability
RELATIVE WP DIFFERENCE	WP of a team relative to WP of the competing team	This variable is an indicator of relative abilities of the competing team
CRUNCH TIME[a] FGA	The proportion of FGA within crunch time	During crunch time, pressure on players is particularly high
COMPETING TEAM'S BLOCKERS	Proportion of FGA where the three best competing team's blockers are on court	This variable is a proxy for the competing team's defense performance in the game
ROUND	Number of the game from a total of 82 games per team in a season	Throughout a season performance can change, for example, through learning
HOME GAME	Dummy variable that equals one if the team of the high performing player plays in the home arena	This variable measures the home game advantage
DECIDED GAME FGA	The proportion of FGA when the game already is decided[b]	In a decided game, teams behave differently since there is no pressure
SHARE OF FT	Proportion of free throws (FT) on all shot attempts (FT and FGA)	This variable is a proxy for the competing team's defense behavior (as well as "the flow" of the game)
COMPETING TEAM'S DEFENSE	The competing team's defensive rating[c] (season average). A smaller value indicates a stronger defense	The competing team's defense ability directly affects the high performing player's team's offense performance
POSITION	Position of the injured high performing player (guard, forward, or center)	The position is related to the role of a player in a team
CLOSE GAME FGA	Proportion of FGA with a score difference of less than six	Close scores can put an additional pressure on players and teams

TABLE 1 (Continued)

Variable	Description	Reason for inclusion as dependent variable
INITIAL SCORE	Score difference at the beginning of the period	The point difference can affect behavior and tactics of a team

[a]We define crunch time as the last 5 min in a game with a score difference of less than six points (https://nba.com).

[b]Similarly to Grund et al. (2013), we identify "give-ups" when the sample probability that a team wins or loses a game given the score at the end of the third quarter (12 min before the end) is equal to 1.

[c]Defensive rating is defined as the number of points a team allows per 100 possessions of the competing team within a game (https://nba.com).

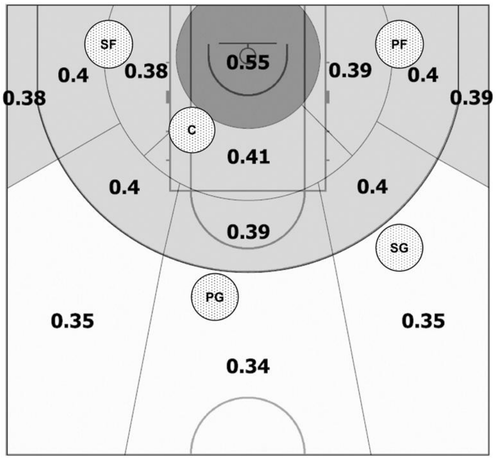

FIGURE 2 Shot chart with average Field Goal Percentages (FG %). Based on NBA seasons 2004/2005 to 2016/2017 and players with at least one whole season in the NBA. The dashed line represents the separation between three point FGA (outside) and two point FGA (inside). Circles with letters correspond to the usual positions (for an exemplary lineup). C, Center; PF, Power Forward; PG, Point Guard; SF, Small Forward; SG, Shooting Guard. *Source*: Own Graph

Our main independent variable is the injury dropout of a high performing player. We assume heterogeneous effects. First, we expect the effects of the injury dropout to positively depend on the skill level of the team (measured by average WP of a team in a given game). In other words, the more skilled a team, the weaker the effect. Second, we analyze the high performing player's position.[6] The difference between guards and forwards is of particular interest: High performing guards are the playmakers and usually lead their team in assists. They help others score and are characterized as "facilitators" (Arcidiacono et al., 2017).[7] High performing forwards are dominant players who dispose of a relatively high offense effectiveness, but their role is less focused on helping others score. In this sense, their way of playing is more self-oriented than in the case of guards. Third, we expect the remaining high performing players to react differently to the injury dropout than average players because remaining high performing players have the distinct skills (and presumably high motivation) to compensate for the injured high performing player.

To complete the models, we include a series of control variables for the season and game context, characteristics of the high performing player, his team, and the competing team.

3.2 | Econometric specification

The econometric model can be expressed in the usual DiD-notation (Angrist & Pischke, 2008):

$$y_{it} = \alpha + \beta_1 d + \beta_2 T + \beta_3 (d \cdot T) + \beta_4 X_{it} + \varepsilon_{it}.$$

y_{it} represents the dependent (performance) variable of game i in period t, with $t \in \{1, 2\}$ for the period before and after the injury dropout. d is a dummy variable indicating whether game i is an injury dropout game or not (injury dropout group vs. control group). T is a dummy variable which equals 0 for the period before the dropout and 1 for the period after the dropout. Hence, the interaction term $d \cdot T$ represents the variable of interest. It is equal to 1 if and only if a high performing player drops out due to an injury. X_{it} is a vector of control variables. β_1, β_2, β_3, β_4 are the coefficient vectors we estimate. We estimate Ordinary Least Squares (OLS) with White heteroskedastic-robust standard errors to avoid inferential bias (Cameron & Trivedi, 2005).[8]

In order to estimate heterogeneous effects of the high performing player's injury dropout, we analyze subsamples (for the position of the high performing player and the effect on remaining high performing players). To capture the effect of the average skill level of the team, we extend the model to a difference-in-difference-in-difference (DiDiD) form (Imbens & Wooldridge, 2007) by multiplying the interaction term $d \cdot T$ with the average WP of a team in a given game.

4 | RESULTS

4.1 | Summary statistics

Table 2 shows the summary statistics. The average FG % is around 0.46. The number of FGA per 48 min is slightly above 80. The expected individual FG % is naturally very close to the average FG % but has a smaller standard deviation. Shot balance averages 0.86.

TABLE 2 Summary statistics

	Mean	SD	Min	Max
FG %	0.456	0.12	0.077	0.929
FGA 48	81.05	12.46	40	132
EXPECTED INDIVIDUAL FG % (IN %)	45.3	3.272	31.13	58.31
SHOT BALANCE	0.858	0.071	0.402	1.112
PROPORTION OF 3S (IN %)	22.99	11.14	0.86	86.67
SCORE 48	97.14	21.7	24	188
PERIOD 2	0.5	0.5	0	1
INJURY DROPOUT GROUP	0.078	0.269	0	1
INTERACTION TERM (PERIOD 2 × INJURY DROPOUT GROUP)	0.039	0.194	0	1
RELATIVE WP DIFFERENCE	1.14	0.814	0.071	18.9
TEAM WP	2.259	2.537	−0.052	9.439
WP OF HIGH PERFORMING PLAYER	10.327	3.961	4.35	23.3
CRUNCH TIME ATTEMPTS	0.005	0.167	0	8
COMPETING TEAM'S DEFENSE	99.61	7.471	82.2	111.9
COMPETING TEAM'S BLOCKERS	0.071	0.127	0	1
DECIDED GAME ATTEMPTS	0.03	0.926	0	41
SHARE OF FT ON TOTAL ATTEMPTS	0.215	0.114	0	0.643
CENTER HIGH PERFORMING PLAYER (DROPOUT)	0.22	0.414	0	1
FORWARD HIGH PERFORMING PLAYER (DROPOUT)	0.397	0.489	0	1
GUARD HIGH PERFORMING PLAYER (DROPOUT)	0.351	0.477	0	1
SHARE OF CLOSE GAME ATTEMPTS	0.455	0.367	0	1
INITIAL SCORE	−0.057	7.332	−25	26
HOME GAME DUMMY	0.493	0.5	0	1
ROUND	41.41	22.45	1	82

Note: Based on $n = 156{,}130$ FGA in 3927 games.

4.2 | Estimation results

Results for the main DiD regression models and the heterogeneous effects are shown in Tables 3 and 4, respectively.

4.2.1 | Efficiency

Given the players' skills and the zone of the court a FGA is taken from, there is no significant effect of the injury dropout on FG % in all estimated models. This result can be explained by the ability of the elite NBA players to achieve a stable level of efficiency in a wide range of situations. Additionally, FG % in a given situation may not depend on effort and therefore is less prone to behavioral effects (Berri & Krautmann, 2006).

4.2.2 | Risk taking

The expected individual FG %, that is, the ex-ante likelihood of a FGA taken by a given player from a particular zone of the court being successful, slightly but significantly decreases after the dropout. This means that players increasingly take FGA from zones where their expected FG % is relatively smaller. We propose four explanations for an underlying mechanism. First, players might exert less effort to get into such positions. Second, they try to

TABLE 3 Regression results of difference-in-difference models

	FG %	FGA 48	Expected FG %	Shot balance	Score 48
PERIOD 2	−0.017*** (0.003)	6.993*** (0.249)	−0.253*** (0.078)	−0.002 (0.002)	6.564*** (0.497)
INJURY DROPOUT GROUP	−0.004 (0.007)	4.175*** (0.631)	0.77*** (0.211)	−0.008 (0.005)	1.973 (1. 274)
INTERACTION TERM (PERIOD 2 × INJURY DROPOUT GROUP)	**0.016 (0.01)**	**−8.812*** (0.873)**	**−0.509* (0.297)**	**−0.003 (0.008)**	**−6.147*** (1.839)**
TEAM WP	−0.0001 (0.001)	−0.044 (0.046)	0.07*** (0.015)	−0.0004 (0.0003)	0.147 (0.093)
REL. WP DIFFERENCE	−0.001 (0.001)	0.059 (0.016)	0.008 (0.05)	−0.002* (0.001)	1.187*** (0.278)
COMPETING TEAM'S DEFENSE	0.0001 (0.0002)	0.13*** (0.016)	−0.003 (0.005)	0.0003*** (0.0001)	0.331*** (0.032)
COMPETING TEAM'S BLOCKERS	−0.008 (0.01)	1.295 (0.962)	−0.015 (0.283)	−0.009 (0.008)	−0.366 (1.869)
CRUNCH TIME ATTEMPTS	−0.011 (0.008)	0.48 (0.638)	0.062 (0.252)	−0.001 (0.006)	0.0108 (2.236)
CLOSE GAME ATTEMPTS	−0.0003 (0.004)	−1.076*** (0.321)	0.089 (0.101)	−0.002 (0.002)	−1.863*** (0.615)
DECIDED GAME	0.001 (0.001)	0.048 (0.105)	−0.038 (0.037)	0.001* (0.001)	0.265* 0.151
SHARE OF FT ON TOTAL ATTEMPTS	−0.024* (0.012)	−51.88*** (1.032)	0.785** (0.327)	−0.06*** (0.007)	27.35*** (2.076)
AVERAGE ZONE FG %	0.007*** (0.001)				0.662*** (0.1)
INITIAL SCORE	−0.0003 (0.0002)	-0.012 (0.08)	−0.001 (0.005)	0.0001 (0.0001)	−0.338*** (0.033)
HOME GAME DUMMY	0.003 (0.003)	−0.331 (0.235)	−0.008 (0.074)	0.001 (0.002)	2.6*** (0.474)
ROUND	0.0002*** (0.0001)	−0.002 (0.005)	0.001 (0.002)	0.000 0.000	0.049*** (0.011)
CONSTANT	0.113*** (0.032)	76.43*** (1.652)	45.29*** (0.52)	0.842*** (0.012)	20.67*** (5.554)
N	7854	7854	7854	7854	7854
Adj. R^2	0.028	0.31	0.01	0.012	0.078

Note: Robust standard errors in parenthesis. Bold values indicate the variable of interest.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE 4 Heterogeneous effects of injury dropouts (interaction term PERIOD 2 × INJURY DROPOUT GROUP)

	FG %	FGA 48	Expected FG %	Shot balance	Score 48
Subsamples					
Injury dropout of high performing centers	−0.007 (0.026)	−5.318** (2.323)	−0.339 (0.748)	0.003 (0.022)	−6.504 (5.059)
Injury dropout of high performing forwards	0.017 (0.016)	−8.158*** (1.345)	0.472 (0.409)	0.003 (0.012)	−4.654* (2.791)
Injury dropout of high performing guards	0.023 (0.015)	−10.68*** (1.321)	−1.609*** (0.488)	−0.011 (0.011)	−7.79*** (2.78)
Remaining high performing players	0.021 (0.022)	2.339** (0.932)	0.147 (0.446)	–	–
Injury dropout of high performing player by 85 percentile	0.017 (0.012)	−7.706*** (0.966)	−0.436 (0.347)	−0.006 (0.009)	−5.444*** (2.146)
Injury dropout interacted with average team WP					
INTERACTION TERM (PERIOD 2 × INJURY DROPOUT GROUP)	0.006 (0.012)	−9.414*** (1.016)	−0.903** (0.353)	0.001 (0.008)	−7.675*** (2.19)
INTERACTION TERM (...) × WP TEAM	0.005 (0.003)	0.269 (0.245)	0.176** (0.079)	−0.002 (0.002)	1.108** (0.527)

Note: Robust standard errors in parenthesis.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

compensate for the injury dropout of the high performing player by increasing risk through shifting to more three point FGA that, on average, are riskier than two point FGA (Figure 2). However, we do not find a significant increase in the proportion of three point FGA on total FGA after the injury dropout (Table A2 in Appendix). Third, after the injury event, the players have to play in positions that are less suitable for them. Fourth, remaining players are unable to get into promising positions for FGA, because the valuable input by the injured high performing player is missing. This last possibility finds justification in the observation that the decrease in expected individual FG % is driven by the dropout of high performing guards, who are facilitators. The risk increase after the dropout negatively depends on the average team WP. In contrast, we do not observe any significant effect on risk taking of remaining high performing players (although the coefficient is basically the same as in the main model). They seem to be able and willing to maintain expected FG %.

4.2.3 | Output

We find a significant negative effect of the high performing player's dropout on output. This effect is strongest if a high performing guard drops out. Again, this is consistent with the facilitating nature of high performing guards, that is, their team-oriented role (e.g., by passing the ball quickly to players in a promising shooting position). In addition, the average WP of the team does not have an effect on output. Interestingly, remaining high performing players increase their output. They seem to try to step in after the dropout. Since the effect in the main model is significantly negative, however, they do not manage to fully compensate.

4.2.4 | Task allocation

We find shot balance unchanged after the injury dropout, meaning that FGA are similarly distributed before and after the injury dropout in all models.

4.2.5 | Team outcome

Points scored per 48 min significantly decline. We attribute this effect to the decline in output. This effect is mainly driven by the dropout of high performing guards. In addition, the decline is smaller for teams with a higher average WP.

4.3 | Robustness analysis

In order to assess the robustness of our results, we run a series of additional tests. First, our results are robust against different approaches of correcting standard errors to avoid inferential bias, such as clustering or bootstrapping. Second, our results do not change if we apply various specifications of fixed effects for the high performing player's team and the competing team in a given season. Third, we narrow the high performing players to the top 15% of the WP distribution, without changing our results.[9] Fourth, our findings are robust against many different specifications and definitions of control variables. In fact, we can reproduce very similar results using a simple DiD specification without control variables (Table A1 in Appendix). Accordingly, results do not change if we remove all variables that are potentially prone to multicollinearity in terms of high variance inflation factors or to endogeneity. Fifth, we find no differences in our estimates when we exclude observations in late season games, where incentives for teams to win may be different with regard to post season (play-off) pairings or a favorable draft position (Ishak & Ballard, 2012; Walters & Williams, 2012). Sixth, if we ignore the substitute for the high performing player, results do not change. This indicates that our results are not driven by a less skilled player entering for a highly skilled player. Although we find significant differences in the performance of the high performing player and his direct substitute, they are too small to explain our results. In other words, the magnitude of our results can only be explained if remaining players change their performance. Seventh, we find similar results when we use an alternative performance metric to define the high performing player (Player Efficiency Rating, PER). PER is a popular measure of a player's per-minute productivity that combines a variety of individual performance statistics over one season. It is strongly related to scoring and shooting but does only weakly correlate with a team's winning percentage. The only difference in the results when using PER is that after the dropout of a high performing player task allocation becomes more even. This is plausible since PER is highest for very dominant players that take a lot of shots. Eighth, we split the positions of HPTM into smaller subgroups in order to separate point guards from shooting guards. We find that the effects are driven by point guards only, while the results for shooting guards resemble forwards. In addition, this result is robust against the use of alternative data on players' positions.[10] Finally, our results do not change if we try different requirements regarding the definition of a high performing player in terms of games played and average minutes per game. Overall, our results are robust against various alternative specifications and definitions.

5 | DISCUSSION AND CONCLUSION

Teamwork with complex interaction patterns and skill heterogeneity is prevalent in many industries. Thereby, HPTMs make large individual contributions to team performance. In addition, they can influence performance of other team members through peer effects. Using data from professional basketball, we show that after an unexpected, sudden dropout of a HPTM, remaining team members slightly increase risk and reduce individual output. As a result, team outcome declines. We observe heterogeneity in these effects: First, the effects are mainly driven by HPTMs in integrative, team-oriented roles. Second, remaining HPTMs react differently to the sudden absence of their HPTM. They increase their output and otherwise maintain a stable performance. Third, the average skill level of a team losing its HPTM does attenuate the effects on risk taking and outcome.

These results extend previous findings on peer effects in several ways. First, we study reciprocally interdependent production in a real world context, which so far has received little attention in research on peer effects in teams. In this way, we add to the manifold results on peer effects in less interdependent or sequential team production. Next, we explicitly focus on peer effects of the subgroup of HPTMs as an important element of a team. Further, the use of multiple performance measures as well as the inclusion of heterogeneity of skills and roles allows us a differentiated and detailed view on peer effects. For instance, we extend Oettl's (2012) concept of helpfulness as a social dimension to reciprocally interdependent team production by showing that the observed peer effects are driven by facilitating HPTMs with an integrative role in the team. High individual productivity does not necessarily mean large positive peer effects and therefore, not all HPTMs contribute disproportionally to team performance (Berri & Krautmann, 2006). Eventually, our analysis of the immediate reaction to the unexpected, sudden absence of a HPTM clearly differs from other studies examining effects of absenteeism of important team members (e.g., Chen & Garg, 2018; Stuart, 2017) where teams have time to adapt and prepare, for example, by practicing.

Our estimates do not allow us to explicitly disentangle the underlying mechanisms for the observed peer effects. What possibly limits the scope for behavioral explanations is that individual performance in professional basketball is constantly observed by peers, the management, and spectators. Social pressure is constantly high, presumably preventing social loafing (Osborn et al., 2012). Nonetheless, especially non-HPTMs may decrease their effort while blaming the absence of the HPTM for an inferior individual performance. Reduced effort could explain the result of lower output and higher risk because compensating for the injured HPTM requires additional (costly) effort. Besides peer effects, other mechanisms could explain our results. One alternative explanation bases on the fact that after the dropout of the HPTM, tasks have to be redistributed among team members. This may lead to a less effective specialization and thus inferior performance. This explanation gets support from the comparison of positions of the HPTMs and their substitutes, where in only 75% of cases, the positions match. In addition, other team members might have to adjust their tactical role in the team regardless of their position. However, we examine only dropouts of single players. Hence, only one of five players needs to be replaced thereby possibly limiting the tactical implications on each individual player. Further, due to the generalist skills of most basketball players and their ability to perform on multiple positions and taking on multiple roles, reallocating the remaining players does not necessarily result in less effective specialization. Another mechanism that could explain our results bases on strategic responses by the team. For example, the team could willingly slow the pace down, which would result in less FGA and less points scored. While we have no data to test this additional mechanism, we argue that, given the observability and measurability of individual performance combined with the highly competitive environment, each player keeps focusing on his individual output. In addition, the existence of a 24 s time limit for a team's ball possession ("shot clock") restricts the scope for a strategic response. A more likely line of reasoning therefore relies on the facilitating nature of (some) HPTMs. Our results clearly point in that direction because the observed peer effects are mainly driven by HPTMs with a rather team-oriented role. Constant and reciprocal interaction with such team members is a direct channel for peer effects through facilitation. Non-high performing team members profit when the HPTM creates promising opportunities for them (where their marginal product is relatively higher). In other words, there is a complementary relationship between HPTMs and their non-high performing peers in that performance of one team member depends on the inputs of (high performing) peers (Oettl, 2012). In contrast, the subgroup of all HPTMs in a team, besides being complements as well, face a certain level of within-team competition among each other. Highly talented team members strive for recognition, promotion, and better contracts. They may recognize the sudden absence of a HPTM as a window of opportunity to step out of the HPTM's shadow. Their marginal products increase and they can signal their high value to the team (Gould & Winter, 2009).

To gain further insights into potential mechanisms for peer effects of HPTMs in reciprocally interdependent team production, future research could focus on effort levels and routines. In the present empirical setting, this would include measurement of distance covered, running speed, or pass patterns by using tracking data. A second promising research question in this context includes the value of HPTMs in special circumstances, such as situations of particularly high pressure or critical phases during a team task. Eventually, medium term effects of missing HPTMs on team performance examined by Chen and Garg (2018) could be complemented with insights on how other team members adapt to the changed situation.

Our study has certain limitations. There are some important control variables we cannot consider because adequate data was not available. We are not able to fully control for tactical responses of coaches during a given game or strategic behavior in different situations (e.g., giving certain important players a rest with regard to an important subsequent game or advising the team to slow the pace down). Also, we only have limited possibilities to control for the (change in) defense behavior of the competing team. As mentioned before, we therefore cannot attribute our results to peer effects only. The basketball setting has certain peculiarities, potentially limiting generalizations of our results to other organizations. For instance, NBA teams consist of the world's best players with well above average salaries. In addition, basketball provides fast paced and turbulent environments with a high level of observability in terms of performance. Previous research, however, acknowledges the transferability of results from sports (and explicitly basketball) to other industries (Chen & Garg, 2018; Day et al., 2012; Keidel, 1985). Thereby, it is clear that our results mainly apply to contexts with similar characterizing levers, such as reciprocal interdependence, a constant structural working environment, measurability of performance, and different roles of team members in the production process.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ENDNOTES

[1] Some examples include packing envelopes (Falk & Ichino, 2006) or solving anagrams and playing computer games (Flynn & Amanatullah, 2012).

[2] We obtain WP from Rod Fort's Sports Business Data (https://sites.google.com/site/rodswebpages/codes). We thank an anonymous reviewer for referring us to this highly valuable reference.

[3] Forty percent corresponds to the bottom 25% percentile of the distribution of the high performing player's relative court time compared to his season average.

[4] This additional analysis is available from the authors upon request.

[5] Shot balance is calculated as follows: $SB_i = \sum_i s_i \log s_i / \sum_i m_i \log m_i$ with s_i and m_i representing the proportions of shots and minutes of player i in a given game (Chen & Garg, 2018).

[6] In basketball, a lineup consists of five players in the following positions (Figure 2): Two guards (point guard and shooting guard), two forwards (small forward and power forward), and one center.

[7] Arcidiacono et al. (2017) attribute the "facilitator" role mainly to point guards (in contrast to shooting guards, whose behavior resembles those of forwards). We cover this additional distinction in the robustness analysis.

[8] In DiD-models, the common trend assumption is central for identification (Angrist & Pischke, 2008). We argue that absent any injury dropout, the two groups would, on average, have evolved the same way for the following reasons: First, the injury dropout of the high performing player is exogenous and therefore the selection of injury dropout games is random. Second, we exclude all games which could have evolved differently, for example, due to multiple dropouts of high performing players. Third, we use a series of control variables in our models to capture potential differences between groups and periods.

[9] Because of a decreasing sample size, we could not narrow down the definition of the HPTM any further. Using the top 15% of the players, the coefficient for the injury dropout in the model for risk taking turns insignificant. However, the coefficient using the top 20% of the players is significant only on the 10% level. In addition, for both definitions of the high performing player the coefficients are significant at the 1% level in the models using high performing guards.

[10] Players' positions partially differ depending on the data source. We therefore additionally carried out the analysis using position data from the same source where we obtained players' Wins Produced (https://sites.google.com/site/rodswebpages/codes).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

TABLE A1 Regression results of simple difference-in-difference models (without controls)

	FG %	FGA 48	Expected FG %	Shot balance	Score 48
PERIOD 2	−0.018*** (0.003)	6.998*** (0.282)	−0.26*** (0.075)	−0.002 (0.002)	6.784*** (0.502)
INJURY DROPOUT GROUP	−0.003 (0.007)	−4.825 (0.725)	0.76** (0.221)	−0.007 (0.005)	2.211* (1.325)
INTERACTION TERM (PERIOD 2 × INJURY DROPOUT GROUP)	**0.015 (0.01)**	**−9.847*** (1.005)**	**−0.516* (0.295)**	**−0.003 (0.008)**	**−5.221*** (1.899)**
CONSTANT	0.464*** (0.002)	77.554*** (0.196)	45.39*** (0.055)	0.859*** (0.001)	93.78*** (0.346)

TABLE A1 (Continued)

	FG %	FGA 48	Expected FG %	Shot balance	Score 48
N	7854	7854	7854	7854	7854
Adj. R^2	0.005	0.073	0.004	0.001	0.022

Note: Robust standard errors in parenthesis. Bold values indicate the variable of interest.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE A2 Regression results of difference-in-difference model for the proportion of 3s as dependent variable

	Proportion of 3s (in %)
PERIOD 2	2.271*** (0.262)
INJURY DROPOUT GROUP	1.473** (0.656)
INTERACTION TERM (PERIOD 2 × INJURY DROPOUT GROUP)	**0.069 (0.989)**
TEAM WP	0.104* (0.049)
REL. WP DIFFERENCE	−1.034*** (0.144)
COMPETING TEAM'S DEFENSE	0.262*** (0.017)
COMPETING TEAM'S BLOCKERS	−1.386 (0.999)
CRUNCH TIME ATTEMPTS	−0.325 (0.682)
CLOSE GAME ATTEMPTS	−1.228*** (0.34)
DECIDED GAME	−0.069 (0.193)
SHARE OF FT ON TOTAL ATTEMPTS	−1.139 (1.117)
INITIAL SCORE	−0.018 (0.018)
HOME GAME DUMMY	0.13 (0.252)
ROUND	0.011* (0.006)
CONSTANT	−3.042* (1.733)
N	7854
Adj. R^2	0.046

Note: Robust standard errors in parenthesis. Bold values indicate the variable of interest.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.