Interactions of learners and competitors with stars and the implications for organizational performance

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ABSTRACT

Prior research presents conflicting findings about a star employee's influence on her colleagues. We reconcile these findings by shifting the focus from stars to non-stars. Contrary to prior research that treats non-stars as homogenous, we argue that they are heterogeneous. We classify them into learners and competitors and argue that social comparison processes underlie their interaction with stars. Using data from the National Basketball Association, we find that the presence of stars in the organization improves the performance of learners. The change in performance of competitors depends on experience. With senior stars in the organization, junior competitors improve while senior competitors do worse. We also argue that the learning and competitive mechanisms jointly lead to an inverted U-shaped relationship between the ratio of learners to competitors and organizational performance. This study contributes to the micro-foundations of strategy by calling attention to the less-celebrated non-stars in organizations.

Keywords:

Human capital; social comparison; micro-foundations; organizational performance

INTRODUCTION

The literature on star performers in organizations presents mixed findings on how they influence colleagues in collaborative activities. On the one hand, stars help non-stars foster more innovation (Grigoriou & Rothaermel, 2014), provide information through their social ties (Oldroyd & Morris, 2012), and share knowledge with non-stars (Ichniowski & Preston, 2014). On the other hand, stars can hinder group effectiveness (Groysberg, Polzer, & Elfenbein, 2011) and control resources which restricts opportunities for non-stars (Kehoe & Tzabbar, 2015). Highlighting these mixed findings, Call, Nyberg, and Thatcher (2015: 631) note that "Although there are conflicting findings regarding stars' effects on colleagues, there is little understanding of why there are different effects."

In this study, we attempt to reconcile the conflicting findings about the influence of stars on their colleagues. We do so by shifting the focus from stars to non-stars. This shift in focus is necessary because our understanding of when a star's influence on non-stars is positive or negative is limited by the assumption in prior work that non-stars are a homogenous group. Hence, prior work assumes that spillovers from stars have a uniformly positive or negative effect on all non-stars, who are passive recipients of knowledge or information from stars.

Contrary to the assumption in extant research, we argue that non-stars in an organization are heterogeneous. An implication of this heterogeneity is that different types of non-stars may view their star colleague differently that, in turn, creates differences in their interactions with the star. Differences in interactions can impact the performance of both non-stars and the organization. As such, we address two questions in this study: How does the presence of star(s) in an organization influence the performance of different types of non-stars? How does the distribution of different types of non-stars affect organizational performance?

To theorize about the implications of heterogeneity among non-stars, we draw from research on social comparison processes (Festinger, 1954; Buunk & Gibbons, 2007; Nickerson & Zenger, 2008; Obloj & Zenger, 2017). Interpersonal learning and competition are key to social comparison between individuals (Wood, 1989). Yet, research seems to treat them as independent mechanisms in organizations. One set of studies show that organizational members learn from observing their high-performing peers (Sacerdote, 2001;

Falk & Ichino, 2006; Hasan & Bagde, 2013). Other studies show that they compete with peers for access to resources (Herbst & Mas, 2015) and customers (Chan, Li, & Pierce, 2014). We, however, argue that the mechanisms of learning and competition operate simultaneously in organizations.

Our key arguments at the individual level are as follows. When a non-star's performance is much lower than that of a star, she is not likely to compare herself with the star. Rather, such a non-star (whom we call a "learner") would view the star as a role model and aspire for self-improvement (Wood, 1989; Call et al., 2015). In contrast, when a non-star's performance is similar to that of a star, she is likely to compare herself with the star. Whether such a non-star (whom we call a "competitor") is inspired or discouraged by the star's presence depends on her assessment of whether she can attain the star's success (Lockwood & Kunda, 1997). We argue that a competitor's sense of attaining a star's success depends on her experience. A junior competitor would believe that she has ample time to emulate the star. Hence, she may seek self-improvement in the star's presence and is therefore similar to a learner. In contrast, a senior competitor may feel discouraged in the star's presence because there is limited time to emulate the star.

The popular press also provides evidence of learning and competition between stars and non-stars in organizations. Prior to the 2017-18 National Basketball Association season, JR Smith, a capable starter for the Cleveland Cavaliers franchise, hinted at the difficulty in adjusting his role in a team that was trying to best leverage the skills of its superstar, LeBron James (Davis, 2017). In contrast, the languishing careers of Richard Jefferson, Channing Frye, and Kyle Korver were revived when they started playing with LeBron James on the Cavaliers team (Powell, 2017).

We argue that the mechanisms of learning and competition at the inter-personal level jointly affect organizational performance. Specifically, the proportion of learners and junior competitors relative to senior competitors has an inverted U-shaped relation with organizational performance. The underlying tradeoff is as follows. Insofar as learners and junior competitors seek self-improvement in the star's presence, they can improve intra-team coordination and hence organizational performance. In contrast, senior competitors may feel threatened by the star's presence and withdraw from interacting with the star. Such behavior could hinder intra-team coordination and therefore organizational performance.

We test the predictions based on our theory using data from the National Basketball Association (NBA). We find a positive association between the number of stars in the team and the change in performance of learners from the prior period. However, the change in performance of a competitor is contingent on players' league experience. There is a positive (negative) association between the number of senior stars and the change in performance of a junior (senior) competitor. These results confirm the idea that learners and junior competitors are similar in their behavior vis-à-vis stars. Further, we do not find that junior stars affect the performance of either junior or senior competitors significantly. Aggregating to the team level, we find an inverted U-shaped relationship between the proportion of learners and junior competitors relative to senior competitors and the team's overall performance.

Our study advances the management literature on human capital by highlighting the previously overlooked heterogeneity among non-stars. By focusing on heterogeneity among non-stars, we seek to reconcile conflicting findings on the positive and negative effects of stars on their colleagues (Call et al., 2015). In our study, the positive effect of stars on learners and junior competitors, and the negative effect on senior competitors, presents a nuanced view of competition and learning in organizations. By highlighting the performance implications of heterogeneity among non-stars, this study also contributes to the micro-foundations of strategy (Teece, 2007; Abell, Felin, & Foss, 2008; Felin, Foss, & Ployhart, 2015). Theorizing about how heterogeneity among non-stars affects performance at the individual and collective levels provides "a more authentic and dynamic view of teams" (Humphrey & Aime, 2014: 446).

THEORY AND HYPOTHESES

Team production, interdependence, and peer effects

Teams have become ubiquitous in modern organizations (Salas, Cooke, & Rosen, 2008). The need for diverse skills and experience have changed the basis of organizing work from being centered around individual jobs to being centered around team-based structures (Kozlowski & Ilgen, 2006; Kozlowski & Bell, 2013).

A salient feature of a team is interdependence among its members. Interdependence implies that team members can affect each other's output (Thompson, 1967). The literature recognizes the impact of an individual on her fellow team members' outputs as peer effects (Kandel & Lazear, 1992; Mas & Moretti, 2009; Millhiser, Coen, & Solow, 2011; Ichniowski & Preston, 2014).

Thompson's (1967) typology of interdependence suggests that peer effects vary by the type of interdependence. Under pooled and sequential interdependence, there is minimal scope for peer effects due to limited interactions and coordination among team members. Hence, team output closely mirrors the sum of individual contributions. For example, in sports such as baseball or relay races, there is limited task interdependence. As such, the sum of individuals' contributions largely explains team performance.

Under reciprocal interdependence, peer effects are salient since team members work with each other closely through mutual adjustments. For example, in team sports such as basketball, soccer, and hockey, players interact and continuously adapt to each other's actions. In such situations, team output is not the simple sum of the individual contributions of team members but is also a function of their peer effects (Millhiser et al., 2011).

Peer effects of stars

Stars are recognized for their superior performance (Groysberg, Lee, & Nanda, 2008; Call et al., 2015; Kehoe & Tzabbar, 2015; Kehoe, Lepak, & Bentley, 2016). Though there is unanimity about the high individual performance of stars, the literature offers contrasting views regarding their peer effects on colleagues.

On the one hand, a star's colleagues can benefit from accessing her superior human and social capital. A star can help increase the quality of innovation output (Grigoriou & Rothaermel, 2014) and motivate adoption of practices that increase productivity (Lacetera, Cockburn, & Henderson, 2004). A helpful star can improve the quality of publications of non-stars (Oettl, 2012), increase their technical knowledge (Oldroyd & Morris, 2012), and motivate them to achieve higher performance (Mas & Moretti, 2009). On the other hand, a star's privileged access to resources can limit opportunities for non-stars (Kehoe & Tzabbar, 2015). Further, stars' concern for personal status within a group can increase coordination challenges (Groysberg et al., 2011; Swaab, Schaerer, Anicich, Ronay, & Galinsky, 2014).

The contrasting peer effects of stars on their colleagues suggest the need to better understand the conditions under which they are positive and negative (Call et al., 2015). We argue that such an inquiry necessitates revisiting certain assumptions in prior research.

First, the literature has mostly adopted the perspective of stars and treated non-stars as passive recipients of knowledge and information spillovers from stars. Most prior work traces a star's peer effects only to her behavior, i.e., whether she is team-oriented or self-interested (Kehoe & Tzabbar, 2015; Kehoe et al., 2016). This view runs counter to the idea that in a dyadic exchange relationship, both parties influence interactions (Humphrey & Aime, 2014). A consequence of the excessive focus on stars is the view that the positive and negative peer effects of stars operate in isolation of each other.

Second, the literature has assumed that non-stars are a homogenous group. This assumption, however, does not reflect reality on several counts. First, individuals differ in terms of their knowledge, skills, and abilities (Ployhart, Weekley, & Baughman, 2006; Ployhart & Moliterno, 2011). Second, each individual's interpersonal relationships and the opportunities she receives in an organization are unique (Coff, 1997). Third, individuals can exercise discretion in their involvement or effort in a task (Coff, 1997; Coff, 1999). Therefore, assuming that all non-stars are homogenous masks their idiosyncrasies, which are important to recognize when theorizing about the peer effects of stars on non-stars.

The implication of the foregoing discussion is that a star's behavior is not the sole determinant of her peer effects on non-stars. Instead, a star's peer effects comprise two separate processes—a star's inclination to share knowledge and the non-star's response to receive it. Independent of the star's inclination, non-stars can differ in their incentives to cooperate with the star and their ability to absorb knowledge spillovers from her.

In summary, prior research has largely overlooked the contingent effects of heterogeneity among non-stars. Addressing this gap can help develop a more holistic understanding of the effect of stars on their less-celebrated peers. Recognizing that non-stars are heterogeneous and can exercise discretion vis-à-vis a star suggests that they also influence whether a star's peer effects on them are positive or negative. We theorize about the implications of these departures for the performance of non-stars and the organization in the presence of stars.

Heterogeneity among non-stars

While there can be multiple ways to describe heterogeneity among non-stars, we distinguish among non-stars based on their performance relative to a star's performance. Our choice of performance as the distinguishing yardstick is grounded in research on social comparison theory (Festinger, 1954). Individual performance serves as an indicator, albeit an imperfect one, for an individual's ability. Accordingly, we classify non-stars into "learners" and "competitors". A competitor's performance is lower but close enough to a star's performance. In contrast, a learner's performance is far lower than a star's performance; she has some way to go before she can emulate the star's performance.

Before we present our arguments, we highlight the relevance of social comparison theory (including some of its key principles) for our study. First, the theory suggests that individuals have an innate tendency to evaluate their ability "based on comparison with other persons" (Festinger, 1954: 138). Furthermore, "social comparison appears to be embedded deeply into the fabric of organizational life" (Greenberg, Ashton-James, & Ashkanasy, 2007: 23). Translated to our theory, comparison is salient among coworkers in an organization.

Second, an individual's choice of referents is an important consideration. While one can compare with others within and outside an organization's boundary, the former is more likely. The choice of referents is influenced by physical proximity and the degree of interactions (Goodman & Haisley, 2007; Nickerson & Zenger, 2008). Two individuals working on interdependent tasks have much more information about each other than those whose tasks are independent (Goodman & Haisley, 2007). Both proximity and degree of interactions serve to enhance *closeness* among individuals (Wood, 1989; Collins, 1996). Insofar as closeness is more likely within a firm's boundary, coworkers are the more appropriate referents. In our theory, non-stars are more likely to use coworkers as referents.

Third, individuals compare selectively (Festinger, 1954). Upward social comparison (with those better than oneself) is more common and generates stronger behavioral responses than downward comparison (Pfeffer & Langton, 1993; Obloj & Zenger, 2017). In our theory, this insight manifests in learners and competitors comparing themselves with stars rather than the other way. Likewise, competitors are less likely to compare themselves with learners.[1]

Fourth, the extent of comparison is not uniform. It decreases as the difference in ability between two individuals increases (Festinger, 1954). Hence, the greater the (positive) difference between a star and a non-star's performances, the less likely that the non-star would compare herself with a star. In our theory, therefore, competitors are more likely to compare themselves with stars. Learners are unlikely to consider stars as relevant referents due to significant difference in relative performance.

Behavior of learners

We argue that a learner would not feel a sense of competition vis-à-vis a star and instead strive for self-improvement in the latter's presence. Due to the large performance gap, there is little basis for comparison between a star and a learner. The learner would not see herself as a credible peer of the star and not vie for the same set of opportunities or resources as the star. Instead, she may consider the star's superior performance to be a result of significantly higher ability and see the star's presence as an opportunity to improve herself. For example, some mechanisms for self-improvement include making errors and seeking feedback (Wood, 1989; Kozlowski et al., 2001; Buunk & Gibbons, 2007; Goodman & Haisley, 2007). Along similar lines, Edmondson (1999: 351) argues that learning behavior includes "seeking feedback, sharing information, asking for help, talking about errors, and experimenting."

A learner's performance can improve because the star's presence provides both the incentive and the ability to learn. Regarding the incentive to learn, learners could view a star as a role model whose performance they would like to emulate and become future stars (Lockwood & Kunda, 1997). The desire to become future stars can stem from at least two sources. First, star performers earn disproportionately more than non-stars (Rosen, 1981). Second, star performers enjoy greater social capital within the organization and in the labor market (Oldroyd & Morris, 2012; Kehoe et al., 2016).

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[1] A competitor has additional reasons to compare oneself with a star and not with a learner. First, a star earns disproportionately high rewards Rosen (1981) which can motivate some competitors. Second, comparison with learners who are at greater risk of being terminated by the organization serves no purpose.

With respect to the ability to learn, interactions with a star can help a learner improve by leveraging and imbibing a star's superior knowledge and skills. A learner seeking help from a star can leverage the star's central position in the organization's knowledge network (Oldroyd & Morris, 2012), and her superior access to information within and outside the organization (Call et al., 2015; Kehoe et al., 2016). Further, the learner can gain knowledge by observing the star's work practices and through one-on-one interactions (Ichniowski & Preston, 2014).

In sum, we argue that the presence of stars creates both the incentive and ability for a learner to absorb spillovers from stars that, in turn, improves the learner's performance. The likelihood of absorbing spillovers would increase as the number of stars increases. A higher number of stars may not only lead to more but also varied opportunities for interactions and knowledge spillovers to learners. These arguments are consistent with the idea that the impact on performance is more pronounced when the reference group is larger (Obloj & Zenger, 2017). We, therefore, propose the following hypothesis:

> **Hypothesis 1 (H1)**: There is a positive association between the number of stars and the change in a learner's performance from the prior period.

Behavior of competitors

Compared to learners, competitors marginally lag a star in individual performance and would consider themselves similar to stars. Based on Festinger's (1954) theory, similarity in performance implies that competitors are more likely than learners to compare themselves with stars. Further, Festinger's original thesis would predict that when competitors engage in upward comparison with stars, it always creates rivalry between them. Subsequent research, however, suggests that upward comparison leads to more nuanced behaviors (Wood, 1989).

Upward comparison can generate two different effects in an individual (Pelham & Wachsmuth, 1995). On the one hand, it can lead to an *assimilation effect* wherein an individual seeks to construct a sense of similarity with someone better than oneself (Collins, 1996). On the other hand, it can create a *contrast effect* such that comparison with someone better leads to an unfavorable self-image (Mussweiler & Strack, 2000). Both assimilation and contrast effects operate simultaneously in most individuals (Pelham & Wachsmuth, 1995) and organizational situations (Greenberg et al., 2007).

The key question for our theory is: under what conditions would the assimilation effect dominate and when will the contrast effect take precedence for a competitor comparing herself to a star? To address this question, we invoke the notion of *attainability* (Wood, 1989; Lockwood & Kunda, 1997). Whether a competitor assimilates or contrasts with a star depends on her assessment of how likely she can emulate a star's success. A competitor is more likely to assimilate or identify with the star when she thinks that there is enough time to achieve performance that is comparable to a star's or believes that her ability can improve over time (Lockwood & Kunda, 1997). This sense of assimilation would be inspiring for the competitor. It would create a desire for self-improvement and promote inter-personal learning from the star. As such, a competitor seeking self-improvement would exhibit behaviors similar to the learners discussed previously.

On the contrary, a competitor is more likely to contrast with a star when she believes that she does not have sufficient time to improve her ability for emulating the star's performance. Contrast effects can have multiple implications for competitors. First, they could engender a feeling of inferiority and negative self-evaluation (Collins, 1996), thereby creating a sense of threat vis-à-vis the superior referent (Buunk & Gibbons, 2007). Such an individual may feel peer pressure in the presence of a star (Kandel & Lazear, 1992). Second, contrast effects can create a sense of envy. Stars not only have privileged access to resources (Kehoe & Tzabbar, 2015) but also significantly higher visibility inside and outside the organization (Groysberg et al., 2008; Oldroyd & Morris, 2012; Call et al., 2015).

The consequence of contrast effects is that a competitor may limit interactions with the star. Prior work argues that social comparison leading to contrast effects has negative consequences at the individual level (Brown, Ferris, Heller, & Keeping, 2007). For example, an individual may avoid asking for help, admitting errors, or seeking feedback (Brown, 1990; Edmondson, 1999), if she perceives such behavior can expose deficiencies (Dunning, Johnson, Ehrlinger, & Kruger, 2003). Overall, such behaviors can distract from productive efforts to reduce performance (Tai, Narayanan, & McAllister, 2012; Obloj & Zenger, 2017).

We argue that an individual's experience is a valid contingency for assimilation and contrast effects. A junior competitor is more likely to assimilate with a star assuming that she has enough time to emulate a star or improve her ability. In contrast, a senior competitor is more likely to contrast with a star assuming that she is unlikely to emulate the star or does not have sufficient time to improve her ability.

As before, we argue that a competitor's foregoing behaviors would be amplified with an increase in the number of stars in the organization. With more stars, both assimilation and contrast effects would amplify. Higher assimilation and contrast would, in turn, affect a competitor's performance more positively and negatively, respectively. Therefore, we propose the following hypotheses:

> **Hypothesis 2a (H2a):** There is a positive association between the number of stars and the change in a junior competitor's performance from the prior period.
>
> **Hypothesis 2b (H2b):** There is a negative association between the number of stars and the change in a senior competitor's performance from the prior period.

Learning, competition, and organizational performance

We now theorize about how the learning and competitive behaviors of non-stars in the presence of stars aggregate to affect organizational performance. Specifically, we suggest that organizational performance is an outcome of the multiplicative effects of the learning and competitive behaviors of non-stars.

To explicate the multiplicative effects, we argue that organizations face a tradeoff between an individual's learning inclination and competitive behavior. In turn, these behaviors have differing effects on intra-team coordination and ultimately organizational performance. On the one hand, learners and junior competitors have a desire to learn from stars in their quest for self-improvement. As a result, they may increase participation in team production that, in turn, improves intra-team coordination. On the other hand, senior competitors can reduce their commitment to the organization owing to a contrast effect (Brown et al., 2007). Reduced commitment negatively impacts participation in a group (Walumbwa, Cropanzano, & Hartnell, 2009), which can hurt intra-team coordination and organizational performance.

The multiplicative effects lead to an inverted U-shaped performance curve at the organizational level (Haans, Pieters, & He, 2016). Put differently, an optimum proportion of learners and junior competitors relative to senior competitors maximizes organizational performance. As the proportion of learners and junior competitors increases, the marginal positive effect of learning on intra-team coordination may decline. Indeed, research on learning curves suggests that the gains from learning increase at a diminishing rate (Argote & Epple, 1990; Hatch & Dyer, 2004). In contrast, as the proportion of senior competitors increases, competitive behaviors can exacerbate coordination challenges. Hence, extremes of senior competitors or a combination of learners and junior competitors can reduce organizational performance. We, therefore, propose the following hypothesis:

> **Hypothesis 3 (H3):** The ratio of learners and junior competitors to senior competitors has an inverted U-shaped relationship with organizational performance.

METHODS

Empirical context

The context for this study is the National Basketball Association (NBA). Scholars have argued that the world of sports mirrors the world of work as the play structures parallel work structures; in particular, team sports such as baseball, basketball, and football model specific elements of organizational design (Keidel, 1987; Wolfe et al., 2005; Swaab et al., 2014). Moreover, team sports provide relatively controlled field environments and resonate well with practitioners (Staw & Hoang, 1995; Wolfe et al., 2005). Consequently, sports settings are fertile empirical grounds for gaining a deeper understanding of organizational phenomena that are otherwise difficult to measure and evaluate. In this tradition, the NBA has been used as an empirical context to test predictions across studies in management (Pfeffer & Davis-Blake, 1986; Harder, 1992; Staw & Hoang, 1995; Ethiraj & Garg, 2012; Fonti & Maoret, 2016), economics (Berri & Schmidt, 2006; Arcidiacono, Kinsler, & Price, 2017), and psychology (Halevy, Chou, Galinsky, & Murnighan, 2012; Swaab et al., 2014).

The NBA is an appropriate setting to test the predictions of the current study for the following reasons. First, it is a human-capital-intensive context where players are the primary inputs in team production; team performance depends on players' human capital. Second, team production in basketball is reciprocally interdependent since on-court interactions among team members necessitate high coordination and mutual adaptation (Keidel, 1985; Swaab et al., 2014). These interactions result in peer effects among team members. Third, detailed individual-level performance statistics help distinguish stars from non-stars and also capture heterogeneity among non-stars. Finally, team-level data help distinguish between team performance and individual performances.

Sample and data

We obtained detailed data for players and teams from 1991-92 to 2016-17 (hereafter called the 1992 and 2017 seasons, respectively) from Basketball Reference (www.basketball-reference.com). The reliability of NBA data from Basketball Reference is supported by prior academic work (Skinner, 2010; Ethiraj & Garg, 2012; Halevy et al., 2012) and endorsed by leading NBA experts (Kubatko, Oliver, Pelton, & Rosenbaum, 2007). We limited the sample to regular season games (that is, excluded playoff games) to keep the analyses comparable across teams. The final sample comprised 30,414 regular season games over 26 seasons (from 1992 to 2017 seasons) for the 30 teams in the league.

Game-level player performance data include a set of metrics called the "box scores." These include points scored, shots taken, assists made, blocks, turnovers, minutes played and so on. Season-level player performance metrics include value over replacement player and win shares (explained below). Game-level team data include the winning and losing teams, points scored and conceded, home team, and game attendance. To test H3, we aggregated the game-level team data to the season level.

We accounted for the fact that some teams moved to a new city and/or changed their names during the sample period. For example, Vancouver Grizzlies moved to Memphis and became the Memphis Grizzlies in the 2002 season and the New Jersey Nets became the Brooklyn Nets in the 2013 season after moving to Brooklyn. Teams also changed names; New Orleans Hornets became the New Orleans Pelicans in the 2014 season. In all these cases, we treated a team as the same organization because the team essentially remained the same. Changes in its name and/or location did not alter player composition.

To estimate the change in a learner and a competitor's performance (H1 and H2, respectively), we created variables that control for additional measures of individual performance (see Table 1). We obtained these data from Patricia Bender's website (www.eskimo.com/~pbender/), a basketball enthusiast who has collected data over the years. We compiled players' annual salary by triangulating data from Basketball Reference, Patricia Bender's website, and www.espn.com. To make salaries comparable across seasons, we adjusted them using the consumer price index from the Bureau of Labor Statistics. We collected data on the contract status of a player prior to each season (i.e., whether he was a restricted or an unrestricted free agent, or under contract with a team) from the Associated Press news wires, www.nba.com, and www.espn.com. We identified whether a player is a star, a learner, or a competitor based on his annual performance in the previous season (see below). As a result, the final sample for the player-level analyses omitted each player's first season in the league, resulting in 10,575 player-team-season observations.

To estimate team performance (H3), we aggregated the player-level control variables (referred above) to the team-season level to control for the quality of players (see Table 2). We also aggregated game-level player and team statistics to the team-season level. Further, we collected data from Basketball Reference on changes in the head coach of a team and a coach's team-specific experience. For stadium capacity, we used data from www.nbahoopsonline.com and teams' websites. Recall that the measures of learners and competitors are based on their prior season performance. Hence, calculating the ratio of leaners to competitors meant that the first season of each team in the sample was omitted. The final sample comprised 729 team-season observations from 1992-93 to 2016-17.

Insert Tables 1 and 2 about here.

Variables and model specification

Identification of stars, learners, and competitors. Critical to our analyses is identifying a player as a star, learner, or competitor. We bracketed a player in one of these categories using his value over replacement player (VORP) statistic in the prior season *t-1*. That is, the prior season (*t-1*) is the season of identification. VORP reflects a player's net contribution over a fictitious replacement player that the team can hire at a similar cost. Thus, VORP captures a player's importance to the team (Gennaro, 2013). Prior academic work on the NBA validates VORP as an appropriate measure of player performance (Alm, Kaempfer, & Sennoga, 2012).

We classified a player as a star if in season *t-1*, he was above the 90th percentile of the league-wise VORP statistic and played in a majority of games for his team. Identifying stars as top 10% performers at the league-level is reasonable given that by definition, stars are few in number (Rosen, 1981; Aguinis & O'Boyle, 2014). Further, defining a star as someone who played in a majority games for his team in a season ensures that he is a consistent performer.

We now turn to the identification of non-stars as competitors and learners. Per our theory, a competitor is closer in performance to a star than a learner is to a star. Thus, we identified a competitor as someone in the 70th to 90th percentile based on league-wise VORP in season *t-1*. We identified the rest of the players (0 to 70th percentile) as learners. In the context of our theory, three additional issues are critical to identifying competitors and learners.

First, it is possible that a non-star in season *t-1* moves to a new team in season *t*, in which case the change in his performance would confound two effects: peer effects of a star (per our theory) and any effects due to mobility of the focal non-star. To avoid the confound, we used the player-team-season as the unit of analysis and restricted the sample to non-stars who were on the same team in two consecutive seasons.

Second, the results may be biased by changes in the performance of marginal non-stars, that is those who played a limited number of minutes for their team in a season. To avoid the bias, we limited learners and competitors to those players who had played at least 10% of the total possible season minutes. The 10% cut-off for season minutes is conservative.

Third, a player (star, learner, or competitor) may move to a new team(s) due to a mid-season transfer. In these cases, we counted him only in the team where he played the maximum minutes in the season and thus avoided counting him multiple times within a season. This choice assumes that team-level effects on a player's performance are most strongly associated with the team on which he played the most minutes. This assumption is intuitively reasonable as only a fraction of players transfers within a season. Overall, only 5.5% of the player-team observations in the sample involved a mid-season transfer.

***Dependent variables for H1 and H2*:** The dependent variables for H1 and H2 are ΔV, the change in performance of a learner (H1), a junior competitor (H2a), and a senior competitor (H2b) between the current and previous seasons. That is, the current season (*t*) is the season of analyses. We divided competitors into juniors and seniors using the median league-wide player experience (six years) in the sample.

***Dependent variable for H3*:** To test H3 on team performance, the dependent variable is *W,* the average win percentage of a team in season *t*. It is calculated as the ratio of the games won to the games played in the regular season by a team.

***Independent variable for H1 and H2*:** The main explanatory variable is *S*, the number of stars in a team in season *t* based on an individual's performance in season *t-1*.

***Independent variable for H3*:** The main explanatory variable is the ratio of the sum of the count of learners (L) and junior competitors (JC) to the sum of the count of learners and total competitors (C) in a team in season *t*, where C is the sum of junior competitors (JC) and senior competitors (SC). We chose [(L+JC)/(L+C)] as the ratio for two reasons. First, per our theory, both learners and junior competitors seek self-improvement in the presence of stars. Hence, junior competitors are more akin to learners than to senior competitors. Second, C can be zero for a team, in which case the ratio [(L+JC)/C] would be indeterminate and result in loss of observations. Note that the learners and competitors are identified based on their performance in season *t-1*.

***Control variables*:** To test H1 and H2, we controlled for several variables at the player and team levels (see Table 1). Similarly, to test H3 at the team level, we controlled for several team-level variables (see Table 2).

Estimation approach

***H1 and H2*:** We used the Ordinary Least Squares (OLS) model to estimate the association between the number of stars in a team (*S*) and change in a non-star's performance over the previous season (ΔV). We clustered standard errors by the player to account for serial correlation in his performance across seasons. We estimated the change in performance for learners (H1) and competitors (H2a and H2b) using two separate specifications as follows:

$$\Delta V_{ift} \text{ [i.e., } V_{ift} - V_{if(t-1)}] = \beta_0 + \beta_1 S_{f(t-1)} + \Phi_1 P_{1ift} + \Phi_2 P_{2if(t-1)} + \Phi_3 [P_{3ift} - P_{3if(t-1)}] + \alpha_1 F_{1ft} + \alpha_2 F_{2f(t-1)} + \Theta_f + \mu_t + \epsilon_{ift} \quad (1)$$

where the subscripts *i*, *f*, and *t* denote the player, team, and season, respectively. '*i*' denotes a 'learner' (H1), 'junior competitor' (H2a), and 'senior competitor' (H2b). *P* is the vector of player-season-level variables, *F* is the vector of team-season-level variables, Θ_f are team fixed effects to control for unobserved heterogeneity across teams, μ_t are season fixed effects to control for any time-related effects, and € is the error term. Based on the hypotheses, we expect the coefficient estimates for β_1 to be positive for H1 and H2a, and negative for H2b.

***H3*: To estimate the association between the ratio of learners to competitors and team performance, we used the following specification:

$$W_{ft} = \beta_0 + \beta_1 [(L+JC)/(L+C)]_{f(t-1)} + \beta_2 [(L+JC)/(L+C)]^2_{f(t-1)} + \alpha_1 K_{1ft} + \alpha_2 K_{2f(t-1)} + \mu_t + \Theta_f + \epsilon_{ft} \quad (2)$$

where *W* is the average win percentage of team *f* in season *t*, *L* is the number of leaners, *JC* is the number of junior competitors, *C* is the number of competitors (junior plus senior) in the team, *K* is the vector of team-season-level control variables, μ_t are season fixed effects, and Θ_f are team fixed effects. Based on the hypothesized inverted U-shaped relationship, we expect the coefficient estimates for β_1 and β_2 to be positive and negative, respectively. In a robustness test, we treated junior competitors akin to senior competitors and used only the number of learners in the numerator of the ratio.

RESULTS

Heterogeneity among stars, learners, and competitors

In results not presented, we find significant differences between stars and non-stars, and between learners and competitors on individual-level measures such as performance, salary, on-court time, games played as starters, award nominations, and on the likelihood of teams retaining stars, learners, and competitors (see Figure 1). These results suggest that there exists substantial heterogeneity between stars and non-stars (when the latter are treated as a homogenous group), and between learners and competitors (when we recognize heterogeneity among non-stars). Most importantly, these results confirm our premise that all non-stars ought not to be treated as a homogeneous group.

Insert Figure 1 about here.

Descriptive statistics – Hypotheses 1 and 2

Tables 3, 4, and 5 present the descriptive statistics and correlation matrix of variables used to estimate the change in performance of learners, junior competitors, and senior competitors, respectively, in the presence of stars.

Insert Tables 3, 4 and 5 about here.

Main results – Hypothesis 1

Table 6 presents results for H1 which suggests a positive association between the number of stars in a team and the change in a learner's performance across seasons. Focusing on the variables of interest first, the coefficient estimate for the number of stars in Model 3 is positive and significant (p = 0.023), which supports H1. An additional star player improves a learner's performance by 0.053 units, an 11.96% increment over the mean VORP statistic of learners in the regression sample.

Insert Table 6 about here.

With respect to the player-level control variables, a learner's on-court time in the current season is positive and significant (p = 0.000). As one might expect, performance improvement depends critically on the learner getting more opportunities to play. More opportunities can improve performance for at least two reasons. First, more on-court time can help the learner improve his skills (learning-by-doing). Second, interacting with the star in real game situations may help the learner pick up nuances related to basketball plays that improve his performance in the form of peer effects as discussed above.

A learner's league experience has a negative effect (p = 0.001) indicating that a learner has less room for improving performance with increasing experience. Interestingly, a player's change in salary has a negative coefficient estimate (p = 0.000). There are two likely explanations. First, salary increase may make a player complacent. Second, a salary increment is likely due to high performance in the previous season. Therefore, the player may find it difficult to immediately improve performance over the prior season.

Additionally, none of the award nominations have a significant effect on the change in a learner's performance. A couple of explanations might justify these results. First, learners are less likely to receive such nominations. Hence, the fraction of learners receiving these nominations is small. Second, it is possible that the effects of these awards are confounded with other indicators of player quality such as change in individual salary.

With respect to team-level control variables, the coefficient estimate for the team's previous season win percentage is negative and significant ($p = 0.000$). A possible explanation is that after a poor season for the team, players exert more effort in the next season or they become complacent after a good season for the team. In contrast, a coach's team-specific experience has a positive association ($p = 0.058$). Continuity of the coach is a potential indicator of the stability in a team's strategy and routines. Similarly, team salary, an indicator of a team's overall quality of human capital, has an expected positive association ($p = 0.000$) with the change in a learner's performance. A higher quality team would improve a learner's performance, either because other players share their knowledge, or the learner is motivated to emulate the performance of high quality players.

Main results – Hypotheses 2a and 2b

Table 7 presents results for H2 about the change in performance of competitors, controlling for the same variables as in the specification for H1. Per our predictions, junior and senior competitors behave differently in the presence of stars.

Insert Table 7 about here.

Models 1 and 4 present results for the relation between the number of stars in a team and the change in performance of junior and senior competitors, respectively. The results are not significant ($p = 0.132$ for junior competitor and $p = 0.817$ for senior competitors). These non-significant results may be because the effects of junior and senior stars on competitors are confounded. To tease them apart, we split stars also into juniors and seniors using the median league experience of six years, similar to the split for competitors into juniors and seniors.

We first discuss the effect of junior stars on the performance of junior and senior competitors in Models 2 and 5, respectively. The results show that junior stars do not have a significant effect on the performance of junior competitors ($p = 0.281$ in Model 2) or senior competitors ($p = 0.120$ in Model 5). One possible explanation is that competitors may not have enough reason to believe that most junior stars would sustain their high performance. Given a junior stars' shorter tenure, a competitor's evaluation of a junior star may not be reliable or accurate enough (Kulik & Ambrose, 1992; Wood, 1996). The lack of reliability may not trigger either the assimilation effect or the contrast effect in competitors.

These theoretical arguments apart, there is also an empirical explanation in the context of this study. The non-significant results may be because the number of junior stars relative to the number of junior or senior competitors may not be enough for triggering social comparison processes. In our sample, there are zero, one, and two junior stars in 65.5%, 30.2%, and 4.3% of the team-season-level observations, respectively. In comparison, about 60% (75%) of the team-season observations have two or more junior (senior) competitors.

A senior star is likely to have consistent high performance, thus providing a competitor a more accurate basis for comparison. Indeed, our next set of results show that the presence of senior stars has a differential and significant impact on the performance of junior and senior competitors. These results are presented in Models 3 and 6, respectively. The number of senior stars is positively and significantly associated with the change in a junior competitor's performance ($p = 0.013$ in Model 3), which supports H2a, at least for the presence of senior stars. An additional senior star in a team increases a junior competitor's performance by 0.152 units (a 7.77% improvement over the mean VORP statistic of junior competitors in the sample). In contrast, the association between the number of senior stars and the change in performance of a senior competitor is negative and marginally significant ($p = 0.085$ in Model 6), which supports H2b, at least for the presence of senior stars. The (negative) coefficient estimate of 0.070 units implies a 4.23% decline over the mean VORP statistic for senior competitors in the sample. These contrasting results support our theoretical arguments that experience is a valid contingency for upward social comparison. It leads to a possible assimilation effect for junior competitors and a contrast effect for senior competitors.

With respect to the control variables, variables that capture on-court time (both change in on-court time from the prior season and on-court time in the current season) have a positive association with the change in a competitor's performance across models, similar to the results for learners. Likewise, a team's prior season average win percentage has a negative and significant effect for most models.

Most categories of award nominations are insignificant presumably because their effect is captured by the change in a competitor's salary. Interestingly, however, the most improved player nomination has a negative effect on the change in performance of junior competitors (Models 1-3), whereas it has an insignificant effect for senior competitors. This result perhaps suggests that this nomination directly captures a player's improvement in the immediate past. Being nominated can reduce the scope for improvement in the current season and lead to mean reversion for the junior competitor. Nomination to the all-league team has a uniformly positive and significant effect. This nomination suggests that such league-wide recognition, usually the preserve of stars, motivates competitors to perform better.

Descriptive statistics – Hypothesis 3

Table 8 presents the descriptive statistics and correlation matrix of the variables used to estimate team performance. Team performance is positively associated with indicators of team quality but negatively associated with indicators of team instability (due to churn in coaches and players) and limited experience of rookie players.

Insert Table 8 about here.

Main results – Hypothesis 3

Recall that per our theory, a junior competitor (JC) behaves more like a learner (L). As such, we clubbed junior competitors with learners and treated only senior competitors (SC) as competitors for estimating team performance. Table 9 presents results for the association between the ratio (L+JC)/(L+C) and team performance, where C=JC+SC is the total number of competitors.

Focusing on the full specification in Model 4, the coefficient estimates of the ratio are positive ($p = 0.046$) for the linear term and negative for the square term ($p = 0.029$). This result confirms an inverted U-shaped relationship between the ratio and team performance, thereby supporting H3.

Insert Table 9 about here.

The result indicates that a team is likely to perform at its peak when the ratio (L+JC)/(L+C) = 0.733. All else equal, a one-standard-deviation change (0.120 units) in the ratio from the optimum value of 0.733 results in a 0.0067 unit decline in a team's win percentage (see Figure 2). This translates to a 1.35% drop in win percentage for a team that wins half its games on average. This small change can be economically significant for a team. Given the highly competitive nature of the league, a few extra wins matter for a team's progression to the knockout stage of the playoff games. Note that since C = JC+SC, the optimum value of 0.733 for (L+JC)/(L+C) translates to an optimum value of 2.74 for (L+JC)/(SC), that is, the ratio of the sum of learners and junior competitors to senior competitors. Given that the mean number of stars in a team is 1.13 (see Table 8), the value of 2.74 implies that a combination of one star, (say) two senior competitors, and about six junior competitors and learners would maximize team performance.

Insert Figure 2 about here.

To validate the curvilinear (inverted U-shaped) relationship, we checked for two additional conditions (Lind & Mehlum, 2010; Haans et al., 2016). First, the point estimate of the slope is positive at the lower bound of the ratio (0.334; p-value = 0.036) and negative at the upper bound of the ratio (-0.249; p-value = 0.004), respectively. Second, the upper bound of the 95% confidence interval of the optimum ratio [(L+JC)/(L+C) = 0.733 is within the range of the ratio for the regression sample. However, the lower bound of the confidence interval falls outside the minimum value of the range. This result can be explained by the skewness in our team-season sample which leads to inadequate data points on the lower side. Compared to the sum of learners and junior competitors, teams have much lesser senior competitors; our sample has over 65% team-season observations with zero or one senior competitors. We addressed this concern by estimating game-level team performance as it provides us with adequate number of observations (see the next section). With more observations in the game-level analysis, the 95% Fieller confidence interval of the optimum ratio (0.714) is within the range of the ratio for the regression sample. Further, the lower and upper bounds of this interval are at least one standard deviation within the corresponding bounds of the ratio in our regression sample.

With respect to the control variables, the coefficient estimate for a team's prior-season win percentage is positive ($p = 0.001$), likely because teams carry their capabilities (Huckman & Pisano, 2006; Groysberg et al., 2008) and routines (Winter, 1995) to the next season. In contrast, a mid-season change in coach affects team performance negatively ($p = 0.000$), possibly due to disruption of routines and loss of critical human capital. The coefficient estimate for season-level attendance ratio in the home stadium is positive ($p = 0.000$), confirming the intuition that support from fans motivates a team to perform better (Mizruchi, 1985; Courneya & Carron, 1992). Team salary and the count of stars indicate the overall quality of players in the team. Expectedly, both have a positive and significant effect on team performance ($p = 0.004$ for team salary and $p = 0.000$ for stars). In contrast, the count of players on a roster has a negative impact ($p = 0.000$), possibly because more number of players is a signal of churn that lowers team stability and disrupts routines.

Among the aggregate team-level variables for nominations for various player awards, only the nominations for best rookie player has a positive and significant association ($p = 0.000$). In contrast, the nominations for the league's all-rookie team ($p = 0.037$) has a negative effect. These contrasting results could be due to high correlation between the two variables. The non-significant effect of other categories of nominations further indicate two possibilities. First, the count of awards may be too small to have an aggregate level impact on team performance. Second, these nominations reflect the quality of human capital in the team. Consequently, their effects may have been absorbed in the overall indicators of the quality of team-level human capital such as count of stars and team salary.

Robustness tests

We conducted several additional tests to check for the robustness of the main results.

Results for H1 and H2 using alternate identifications of stars, competitors, and learners: The results for the association between the number of stars and the change in individual performance—positive for learners in the presence of stars; positive and negative for junior and senior competitors, respectively, in the presence of senior stars—remain qualitatively similar using other percentile cutoffs for stars, learners, and competitors. These include, for example, (star > 90, competitor 65-90, and learner 0-65), (star > 85, competitor 70-85, and learner 0-70), and (star > 85, competitor 65-85, and learner 0-65) where numbers represent percentiles. The results are available from the authors.

Additional tests for inverted U-shaped relationship (H3): We verified the inverted U-shaped relationship using *game-level* team performance as the dependent variable. The results in Model 1 of Table 10 are similar to those using season-level team performance. Further, game-level data provided adequate observations for analyses that satisfy additional tests for an inverted U-shaped relationship. First, similar to the season-level results, the point estimates of the slope were positive and negative at the lower and upper extremes of the ratio, respectively (Lind & Mehlum, 2010; Haans et al., 2016) (see Model 2). Second, we included the cubic term of the ratio in the specification (see Model 3). The insignificant results for the cubic term do not support the possibility of an S-shaped relationship, thereby further confirming an inverted U-shaped relationship (Haans et al., 2016).

Insert Table 10 about here.

Inverted U-shaped relation (H3) using alternate definition of learners and competitors: To estimate team performance, we created an alternate definition by treating both junior and senior competitors together as competitors. Thus, we modified the ratio in Equation (2) to [L/(L+C)] where L and C are learners and competitors (juniors plus seniors), respectively. The results presented in Table 11 support our arguments for the inverted U-shaped relationship. The main results in Model 1 are similar to those in Model 4 of Table 8. Further, similar to the methodology in Table 10, we used game-level data for the revised ratio and found that the results still support H3 (as shown in Models 2 to 4).

Insert Table 11 about here.

DISCUSSION AND CONCLUSION

In contrast to prior research that has treated non-stars as a homogenous group, this study built on the assertion that there exists heterogeneity even among non-stars, as determined by their relative performance vis-à-vis stars. A critical implication of unpacking heterogeneity among non-stars is that under reciprocally interdependent production, stars do not unilaterally influence the performance of non-stars. Heterogeneity among non-stars can influence whether non-stars learn from stars or compete with them. Drawing from research on social comparison processes, we found that in the presence of stars, learning and competitive behaviors of non-stars have positive and negative impacts on their performance, respectively.

Heterogeneity among non-stars also leads to a tradeoff that affects organizational performance non-linearly. On the one hand, learners and junior competitors improve intra-team coordination as they focus on imbibing knowledge from the star in their quest for self-improvement. On the other hand, senior competitors may experience a contrast effect and reduce participation in the group, thereby adversely impacting intra-team coordiantion. Managing this tradeoff through the lever of team composition (in this study, the combination of learners, and junior and senior competitors) can improve organizational performance.

Contributions

This study contributes to the growing management literature on how star employees influence organizational performance (Groysberg et al., 2008; Grigoriou & Rothaermel, 2014; Kehoe & Tzabbar, 2015). But in contrast to the dominant emphasis on theorizing from the perspective of star performers, this study brings non-stars into the discourse. Prior research has argued that stars influence their colleagues through both a positive, learning effect (Oettl, 2012; Ichniowski & Preston, 2014) and a negative, competitive effect (Groysberg et al., 2011; Swaab et al., 2014; Kehoe & Tzabbar, 2015). While these streams of work make markedly different arguments, they both take a narrow view that non-stars are homogenous and passively receive spillovers from stars. This study urges scholars to recognize that there exists heterogeneity even among non-stars. Recognizing this heterogeneity aligns the academic discussions more closely with the complexities of organizations (Humphrey & Aime, 2014).

This study presents a nuanced view of competition and learning among individuals in an organization. Extant literature suggests that stars only compete with other stars. The results of the current study show that learning and competition in organizations do not operate in isolation, as assumed previously. Rather, they are at play simultaneously. Senior competitors perform worse in the presence of senior stars, presumably due to the contrast effect. However, junior competitors improve their performance in the presence of senior stars, perhaps due to an assimilation effect.

The study also deepens our understanding of the micro-foundations of strategy (Teece, 2007; Nyberg, Moliterno, Hale, & Lepak, 2014; Felin et al., 2015). We emphasize the importance of ordinary employees (non-stars) in determining organizational performance even in the presence of extraordinary employees (stars). Beyond doubt, stars are important (Groysberg et al., 2008; Molloy & Barney, 2015). However, inordinate focus on stars to the relative neglect of non-stars is tantamount to a partial view of organizations.

Implications for practice

The individual-level findings suggest that managers must pay attention to the taken-for-granted notion of 'fit' between different types of employees. This study highlights that learners and competitors react differently to the presence of stars in an organization, which manifests in varying impact on their performance. A corollary is that learners and competitors are not passive recipients of spillovers from stars. Instead, they play an active role in determining their individual and organizational performances. Thus, in their efforts to improve teamwork and organizational performance, managers should also focus attention on how heterogeneous non-stars interact with stars, and not just on leveraging the skills of stars.

The finding that an optimum combination of learners, junior competitors, and senior competitors maximizes organizational performance has implications for organization design. The mechanisms of learning and competition are both important but extremes of either lead to sub-optimal outcomes at the aggregate level. Therefore, managers must recognize that neither too many learners and junior competitors nor too many senior competitors are good for organizational performance. The results of our study suggest that an approximate combination of one star, two senior competitors, and six learners and junior competitors maximizes organizational performance. Based on our converstations, practitioners from other human-capital-intensive contexts (such as software services) find this prescription intuitive.

Limitations

In using data from the NBA to test the predictions, one valid concern is whether the theory is generalizable to other types of business organizations. In this regard, Day, Gordon, and Fink (2012) observe that the contextual overlaps in sport and work can be generalized while Wolfe et al. (2005) highlight that the world of sport mirrors the world of work. Along these lines, we argue that the theory can be generalized to organizations that meet the following conditions. First, they are human-capital-intensive so that one can classify individuals based on their relative performance. Second, team production is reciprocally interdependent such that there are peer effects among team members. Contexts such as surgical teams, product development units, software development groups, and R&D teams readily meet these criteria.

A related concern is that the NBA may be unique in its treatment of stars. First, one may argue that there is excessive attention on NBA stars, unlike in many other contexts. But such attention is also evident for star surgeons, scientists, money managers, or lawyers. Second, it seems that NBA stars go through excessive scrutiny by the media and spectators, which may not be true for stars in other contexts. But the finance industry publishes annual All-Star lists (Groysberg et al., 2008) and websites rate doctors (Bacon, 2009). Third, stars and non-stars in the NBA have shorter career spans compared to other professions. The last concern, however, only makes the findings of the current study more conservative. If employees have longer tenures in other business organizations, non-stars are likely to get more opportunities to learn from or compete with stars. Therefore, in other business organizations, the peer effects of stars may be even more pronounced and sustained.

While we have included several control variables that rule out multiple alternative explanations, our results do not empirically identify the mechanisms of inter-personal learning and competition in a granular manner. More broadly, the effect of one peer on another is inferred rather than empirically tested. This limitation, however, seems to afflict most of the empirical literature on peer effects (Angrist, 2014). We continue to look for more fine-grained data and better ways to test the mechanisms in subsequent revisions of the paper.

Conclusion

In summary, this study turns the spotlight to ordinary organizational members while preserving the importance of the extraordinary. We urge scholars and practitioners to not turn a blind eye to non-stars. They are not merely bricks in the wall; rather they are critical pieces in the jigsaw puzzle called organizations. Recognizing the importance of learners and competitors, and optimizing the tradeoffs associated with them, can help organizations derive human-capital-based benefits beyond those derived from stars.

Figure 1: Survival estimates for stars, learners, and competitors

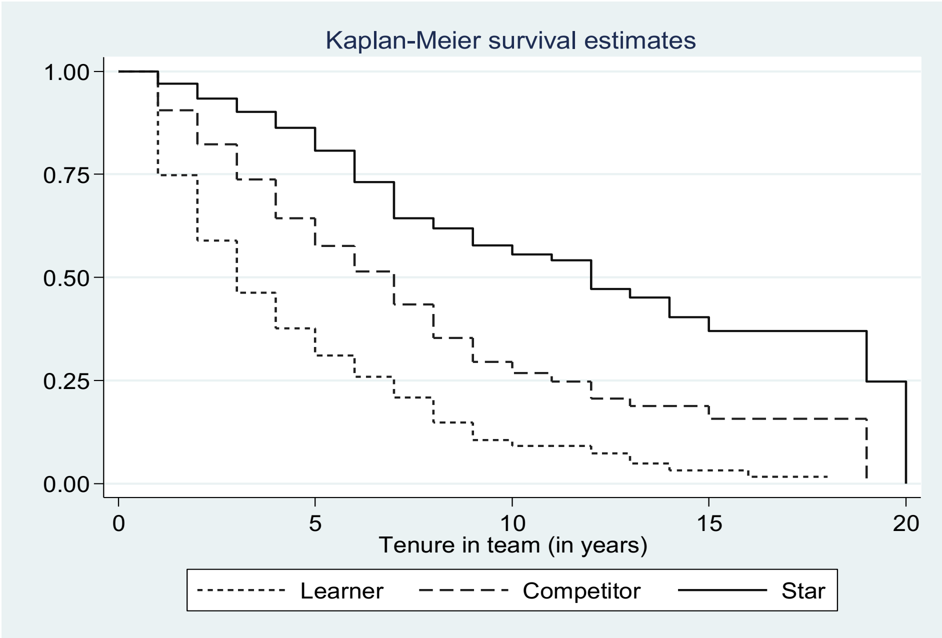
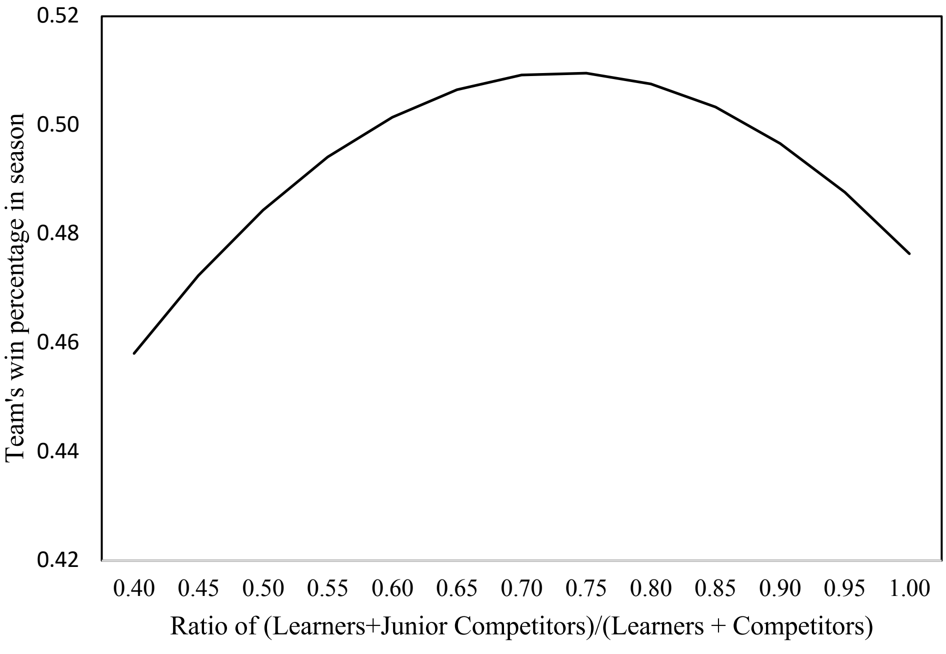


Figure 2: Team win percentage as a function of the ratio of learners to competitors



Note: Inverted U-shaped relationship calculated using mean values of control variables; 'Competitors' is the sum of junior and senior competitors.

Table 1: Control variables used in the specifications to estimate the change in a player's individual performance

Variable	Description	Reason for inclusion
Change in playing time over last season	Change in time played during regular season over last season in the team	Opportunity to play is critical for improvement in a player's performance
Time played in the team in current season	Total time a player was on court for the team	Playing time in the team influences peer effects, that is, the scope for learning or competition
Change in player's salary	Change in the player's salary over last season	Influence of incentives on a player's performance; correlated with improved performance in the past
Player's league experience	Player NBA experience in years	Player's league experience can reflect potential/ability to absorb spillovers
Player's experience in the current team	Player team-specific experience in years	Familiarity with team-specific routines (firm-specific human capital) can affect a player's performance
Player is a free agent	Binary variable: Equals one if the player is a restricted or unrestricted free agent	Player's contract status can affect the extent of his involvement in the team and hence performance
Best defensive player nomination	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of past performance; can affect a player's current performance
Best sixth man nomination	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of past performance for a player with limited opportunities; can affect current performance
Most improved player nomination	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of a player's improvement in the past; can affect a player's current performance
Most valuable player nomination	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of a player's quality; can affect a player's current performance
Best rookie nomination	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of a newcomer's ability; can affect his opportunities to play and hence current performance
Nomination to All-Defensive team	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of recognition for past performance; can affect a player's current performance
Nomination to All-Rookie team	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of recognition for past performance; can affect a player's current performance
Nomination to All-League team	Binary variable: Equals one if the player was nominated; lagged by one year	An indicator of recognition for past performance; can affect a player's current performance
Team win percentage (previous season)	Ratio of wins to total games in the regular season; lagged by one year	Indicator of the quality of team's routines, players, and staff; can affect a player's current performance
Coach's experience in the current team	Coach's team-specific experience in years	Indicator of stability in a team's strategy and routines
Number of learners in the team	Count of learners in the team; Learners identified based on previous year performance	Can influence peer effects and thus a player's current performance
Number of competitors in the team	Count of competitors in the team; Competitors identified based on previous year performance	Can influence peer effects and thus a player's current performance
Team salary	Total salary paid to all players on the roster; adjusted for CPI	Proxy for overall quality and experience of peers in the team; can affect a player's current performance

Table 2: Control variables used in the specification to estimate team performance

Variable	Description	Reason for inclusion
Team salary	Total salary paid to all players on the roster; adjusted for CPI	Proxy for effect of overall quality and experience of players; can affect team performance
Number of stars in the team	Count of star players on team roster	Number of stars reflect a team's human capital; can affect team performance
Number of players on the team roster	Total number of players in the team	Size of team roster indicates team stability and opportunities for players to play
Team tenure of stars	Average team-specific tenure (in years) of star players	Tenure of star players can affect team interactions and hence team performance
Team tenure of learners + junior competitors	Average team-specific tenure (in years) of learners and junior competitors	Tenure of learners and junior competitors can affect team interactions and hence team performance
Team tenure of senior competitors	Average team-specific tenure (in years) of senior competitors	Tenure of senior competitors can affect team interactions and hence team performance
Number of players on All-Defensive team	Count of players in the NBA All-Defensive team; lagged by one year	Best defensive players in the league can affect team performance
Number of players on NBA All-Rookie team	Count of players in the NBA's All-Rookie team; lagged by one year	Best rookie players in the league can affect team performance
Number of players on NBA All-League team	Count of players in the NBA's All-League team; lagged by one year	Best players of the league can affect team performance
Number of best defensive player nominations	Count of players nominated for the award; lagged by one year	Best defensive players in the league can affect team performance
Number of most valuable player nominations	Count of players nominated for the award; lagged by one year	Most valuable players in the league can affect team performance
Number of best sixth man nominations	Count of players nominated for the award; lagged by one year	Best sixth men in the league indicate bench strength that can affect team performance
Number of most improved player nominations	Count of players nominated for the award; lagged by one year	Most improved players in the league can affect team performance
Number of best rookie player nominations	Count of players nominated for the award; lagged by one year	Best rookie players in the league can affect team performance
Attendance to stadium capacity ratio (season)	Ratio of average attendance in home games to stadium capacity	Attendance in home games can add to a team's home advantage and improve team performance
Coach's experience in the current team	Coach's team-specific experience in years	Coach's tenure indicates stability in a team's strategy and routines
Coach change during the season	Binary variable: Equals one if a team's coach changed during the season	Change in coach can disrupt a team's strategy and routines that can affect team performance
Team win percentage (previous season)	Ratio of wins to total games in the regular season; lagged by one year	Team's past performance can affect its current performance

Table 3: Descriptive statistics and correlation matrix of variables to estimate change in the performance of learners in the presence of stars

S No.	Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1	Change in learner's performance	0.249	0.862	-1.965	7.547	1							
2	Number of stars in the team	1.020	0.965	0	4	-0.030	1						
3	Change in playing time over last season	0.929	6.887	-20.980	24.220	0.544	0.022	1					
4	Time played in the team in current season	15.196	6.873	2.396	33.950	0.483	-0.077	0.583	1				
5	Change in player's salary	0.206	0.463	-2.391	3.111	-0.041	-0.006	0.028	0.048	1			
6	Player's league experience	5.776	3.561	2	21	-0.148	0.135	-0.168	-0.093	-0.205	1		
7	Player's experience in the current team	3.059	1.703	1	20	-0.031	0.046	-0.043	0.035	-0.070	0.307	1	
8	Player is a free agent	0.257	0.437	0	1	-0.056	0.070	-0.033	-0.147	0.005	0.145	0.010	1
9	Best defensive player nomination	0.009	0.092	0	1	-0.002	-0.013	-0.037	0.020	-0.002	0.015	0.049	0.013
10	Best sixth man nomination	0.037	0.189	0	1	-0.03	0.098	-0.030	0.068	0.014	0.073	0.057	0.001
11	Most improved player nomination	0.041	0.199	0	1	-0.049	-0.008	-0.090	0.081	0.075	-0.064	0.029	0.020
12	Most valuable player nomination	0.001	0.037	0	1	-0.027	0.038	-0.019	-0.001	0.011	0.06	0.086	-0.022
13	Best rookie nomination	0.029	0.168	0	1	0.061	-0.065	0.016	0.167	-0.027	-0.184	-0.109	-0.083
14	Nomination to All-Rookie team	0.023	0.149	0	1	0.057	-0.065	0.018	0.198	-0.040	-0.161	-0.096	-0.084
15	Team win percentage (previous season)	0.476	0.159	0.106	0.890	-0.064	0.684	0.051	-0.067	-0.004	0.223	0.082	0.072
16	Coach's experience in the current team	3.067	2.918	1	21	0.005	0.215	0.002	-0.020	0.007	0.046	0.072	0.053
17	Number of learners in the team	7.857	2.028	2	14	0.003	-0.400	-0.038	-0.012	-0.009	-0.088	-0.029	-0.023
18	Number of competitors in the team	2.029	1.293	0	8	-0.025	-0.045	0.013	-0.062	-0.013	0.076	0.003	0.022
19	Team salary	3.175	0.393	1.883	4.055	-0.038	0.193	0.003	-0.067	-0.039	0.121	0.151	0.041

S No.	Variables	9	10	11	12	13	14	15	16	17	18	19
9	Best defensive player nomination	1										
10	Best sixth man nomination	0.001	1									
11	Most improved player nomination	0.056	0.179	1								
12	Most valuable player nomination	-0.003	-0.007	-0.008	1							
13	Best rookie nomination	0.028	0.009	-0.036	-0.006	1						
14	Nomination to All-Rookie team	0.036	0.019	-0.031	-0.006	0.727	1					
15	Team win percentage (previous season)	0.015	0.122	-0.017	0.049	-0.092	-0.093	1				
16	Coach's experience in the current team	0.007	0.037	-0.020	0.021	-0.024	-0.002	0.283	1			
17	Number of learners in the team	0.003	-0.073	-0.002	-0.029	0.057	0.046	-0.488	-0.177	1		
18	Number of competitors in the team	0.007	0.038	-0.005	0.035	-0.034	-0.048	0.338	0.055	-0.483	1	
19	Team salary	0.047	0.109	0.037	0.025	0.036	-0.02	0.263	0.026	0.004	0.190	1

Notes: N = 2,919; Correlations greater than |0.04| are significant at the 0.05 level or lower; Variables 3 and 4 rescaled dividing by 100; Change in player salary (variable 5) and team salary (variable 19) are adjusted for CPI and rescaled using logarithmic values; Variables 8-14 have binary values. The variables related to NBA All-Defensive team and All-League team are dropped because no learner has received these nominations.

Table 4: Descriptive statistics and correlation matrix of variables to estimate change in the performance of junior competitors in the presence of stars

S No.	Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1	Change in junior competitor's performance	-0.022	1.200	-3.349	7.196	1									
2	Number of stars in the team	0.974	0.904	0	4	-0.023	1								
3	Number of junior stars in the team	0.372	0.557	0	2	-0.049	0.513	1							
4	Number of senior stars in the team	0.602	0.782	0	3	0.008	0.791	-0.119	1						
5	Change in playing time over last season	-0.791	6.689	-23.110	16.042	0.672	0.028	-0.005	0.036	1					
6	Time played in the team in current season	21.772	6.575	4.470	35.330	0.596	-0.093	-0.035	-0.082	0.683	1				
7	Change in player's salary	0.345	0.528	-0.897	3.098	-0.046	-0.049	-0.057	-0.016	0.040	-0.005	1			
8	Player's league experience	4.258	1.315	2	6	-0.106	0.137	-0.005	0.161	-0.079	-0.079	0.100	1		
9	Player's experience in the current team	3.413	1.315	1	6	-0.020	0.157	-0.018	0.194	0.005	0.017	0.067	0.487	1	
10	Player is a free agent	0.142	0.349	0	1	-0.115	-0.046	-0.059	-0.011	-0.072	-0.144	0.122	0.050	-0.016	1
11	Best defensive player nomination	0.064	0.246	0	1	-0.023	0.112	0.018	0.117	0.011	-0.006	0.074	0.041	0.092	0.009
12	Best sixth man nomination	0.069	0.254	0	1	-0.009	0.051	0.016	0.048	0.061	-0.054	-0.029	0.036	0.038	0.019
13	Most improved player nomination	0.248	0.432	0	1	-0.165	0.072	0.057	0.043	-0.130	-0.015	0.090	-0.011	0.026	0.095
14	Most valuable player nomination	0.028	0.165	0	1	-0.015	0.082	-0.024	0.112	-0.030	0.048	-0.034	0.058	0.084	-0.012
15	Best rookie nomination	0.074	0.263	0	1	0.146	-0.061	0.003	-0.073	0.109	0.083	-0.134	-0.487	-0.305	-0.097
16	Nomination to All-Defensive team	0.023	0.150	0	1	-0.007	0.132	0.035	0.093	0.017	0.023	0.134	0.087	0.102	0.000
17	Nomination to All-Rookie team	0.106	0.308	0	1	0.147	-0.079	0.002	-0.114	0.087	0.096	-0.150	-0.583	-0.370	-0.109
18	Nomination to All-League team	0.020	0.140	0	1	-0.022	0.091	-0.010	0.103	-0.034	0.036	-0.003	0.080	0.073	-0.024
19	Team win percentage (previous season)	0.507	0.149	0.122	0.890	-0.075	0.686	0.262	0.607	0.020	-0.144	0.036	0.195	0.168	0.015
20	Coach's experience in the current team	3.169	3.217	1	21	-0.001	0.13	0.064	0.105	-0.036	-0.111	0.019	-0.032	-0.060	0.055
21	Number of learners in the team	6.873	1.937	2	14	0.010	-0.422	-0.183	-0.357	-0.030	0.048	-0.012	-0.131	-0.098	-0.034
22	Number of competitors in the team	3.026	1.375	1	8	0.020	-0.002	-0.041	0.027	0.019	-0.134	0.050	0.068	-0.004	0.047
23	Team salary	3.185	0.396	2.042	3.987	0.028	0.313	0.092	0.296	0.065	-0.115	0.059	0.155	0.280	-0.002

S No.	Variables	11	12	13	14	15	16	17	18	19	20	21	22	23
11	Best defensive player nomination	1												
12	Best sixth man nomination	-0.045	1											
13	Most improved player nomination	0.052	0.039	1										
14	Most valuable player nomination	-0.004	-0.007	0.065	1									
15	Best rookie nomination	0.003	-0.028	-0.163	0.066	1								
16	Nomination to All-Defensive team	0.269	-0.019	0.014	0.130	-0.020	1							
17	Nomination to All-Rookie team	0.036	-0.048	-0.155	0.074	0.650	-0.019	1						
18	Nomination to All-League team	-0.011	-0.011	0.071	0.239	-0.012	-0.003	-0.011	1					
19	Team win percentage (previous season)	0.141	0.082	0.048	0.111	-0.143	0.097	-0.156	0.065	1				
20	Coach's experience in the current team	0.007	-0.024	0.054	0.004	-0.013	0.026	-0.004	-0.027	0.216	1			
21	Number of learners in the team	0.007	-0.066	-0.041	-0.009	0.116	0.005	0.133	-0.039	-0.518	-0.145	1		
22	Number of competitors in the team	-0.064	0.066	-0.019	-0.011	-0.093	-0.087	-0.125	-0.001	0.384	0.121	-0.548	1	
23	Team salary	0.127	0.123	0.155	0.052	0.004	0.058	-0.114	0.039	0.347	0.065	-0.131	0.230	1

Notes: N = 605; Correlations greater than |0.08| are significant at the 0.05 level or lower; Variables 5 and 6 rescaled dividing by 100; Change in player salary (variable 7) and team salary (variable 23) are adjusted for CPI and rescaled using logarithmic values; Variables 10-18 have binary values.

Table 5: Descriptive statistics and correlation matrix of variables to estimate change in the performance of senior competitors in the presence of stars

S No.	Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1	Change in senior competitor's performance	-0.345	1.117	-3.142	4.545	1							
2	Number of stars in the team	1.240	0.996	0	4	-0.002	1						
3	Number of junior stars in the team	0.407	0.588	0	3	0.004	0.478	1					
4	Number of senior stars in the team	0.833	0.882	0	4	-0.005	0.810	-0.127	1				
5	Change in playing time over last season	-1.958	6.558	-24.584	20.430	0.742	0.025	-0.005	0.032	1			
6	Time played in the team in current season	20.053	6.671	3.637	34.238	0.586	-0.067	-0.056	-0.039	0.682	1		
7	Change in player's salary	0.090	0.333	-1.809	2.269	-0.031	-0.036	-0.019	-0.028	-0.041	-0.013	1	
8	Player's league experience	9.979	2.538	7	19	-0.070	0.136	0.011	0.146	-0.050	-0.109	-0.045	1
9	Player's experience in the current team	4.341	2.755	1	19	0.001	-0.001	-0.044	0.028	0.028	-0.064	-0.068	0.177
10	Player is a free agent	0.218	0.413	0	1	-0.062	0.011	-0.008	0.018	-0.054	-0.143	-0.008	0.155
11	Best defensive player nomination	0.090	0.286	0	1	-0.036	0.091	0.073	0.053	-0.042	0.006	0.021	0.029
12	Best sixth man nomination	0.077	0.267	0	1	-0.039	0.114	0.031	0.109	0.014	-0.134	0.025	-0.014
13	Most improved player nomination	0.052	0.222	0	1	-0.086	0.022	0.043	-0.004	-0.060	-0.010	-0.028	-0.13
14	Most valuable player nomination	0.049	0.216	0	1	0.006	0.048	0.017	0.043	-0.009	0.072	-0.015	0.123
15	Nomination to All-Defensive team	0.057	0.232	0	1	-0.018	0.131	0.062	0.132	-0.007	0.047	0.012	-0.011
16	Nomination to All-League team	0.050	0.219	0	1	-0.012	0.041	0.012	0.044	-0.047	0.070	0.046	-0.004
17	Team win percentage (previous season)	0.573	0.134	0.183	0.890	-0.042	0.634	0.230	0.562	-0.006	-0.099	0.029	0.192
18	Coach's experience in the current team	3.489	3.508	1	21	0.034	0.214	0.102	0.174	0.030	-0.026	-0.070	0.108
19	Number of learners in the team	6.532	1.941	2	14	0.044	-0.348	-0.195	-0.263	0.001	0.026	0.006	-0.076
20	Number of competitors in the team	3.185	1.344	1	8	-0.059	-0.156	-0.031	-0.155	-0.010	-0.091	-0.019	0.040
21	Team salary	3.292	0.397	1.883	4.055	0.043	0.155	0.046	0.145	0.039	-0.087	-0.083	0.105

S No.	Variables	9	10	11	12	13	14	15	16	17	18	19	20	21
9	Player's experience in the current team	1												
10	Player is a free agent	-0.018	1											
11	Best defensive player nomination	-0.013	0.061	1										
12	Best sixth man nomination	0.048	0.076	-0.029	1									
13	Most improved player nomination	-0.039	0.031	0.075	0.092	1								
14	Most valuable player nomination	0.206	-0.066	-0.020	-0.066	0.144	1							
15	Nomination to All-Defensive team	-0.025	-0.047	0.542	-0.020	0.004	0.039	1						
16	Nomination to All-League team	0.034	-0.104	0.003	-0.067	0.173	0.516	0.068	1					
17	Team win percentage (previous season)	0.083	0.073	0.122	0.136	0.009	0.111	0.156	0.098	1				
18	Coach's experience in the current team	0.127	0.089	0.018	0.029	0.004	0.100	0.059	0.025	0.329	1			
19	Number of learners in the team	-0.075	-0.040	-0.032	-0.018	-0.042	0.006	-0.057	-0.026	-0.433	-0.194	1		
20	Number of competitors in the team	0.125	0.010	0.018	0.026	0.037	0.051	-0.003	0.043	0.238	0.078	-0.463	1	
21	Team salary	0.238	0.013	0.130	0.107	0.052	0.07	0.036	-0.002	0.159	0.002	0.041	0.144	1

Notes: N = 634; Correlations greater than |0.08| are significant at the 0.05 level or lower; Variables 5 and 6 rescaled dividing by 100; Change in player salary (variable 7) and team salary (variable 21) are adjusted for CPI and rescaled using logarithmic values; Variables 10-16 have binary values. The variables related to rookie awards and nomination to NBA All-Rookie team dropped because senior players are not eligible for these awards.

Table 6: Change in performance of learners in the presence of stars

OLS model; VORP-based measure of performance **DV: Change in learner's performance**	**1**	**2**	**3**
Number of stars in the team			0.053*
			(0.023)
Change in playing time over last season		0.052**	0.052**
		(0.003)	(0.003)
Time played in the team in current season		0.033**	0.033**
		(0.002)	(0.002)
Change in player's salary		-0.147**	-0.144**
		(0.030)	(0.030)
Player's league experience		-0.014**	-0.014**
		(0.004)	(0.004)
Player's experience in the current team		-0.006	-0.006
		(0.008)	(0.008)
Player is a free agent		-0.007	-0.008
		(0.029)	(0.029)
Best defensive player nomination		0.159	0.169
		(0.160)	(0.159)
Best sixth man nomination		-0.072	-0.077
		(0.068)	(0.068)
Most improved player nomination		-0.095	-0.098
		(0.078)	(0.078)
Most valuable player nomination		-0.373	-0.400
		(0.285)	(0.283)
Best rookie nomination		0.122	0.120
		(0.108)	(0.109)
Nomination to All-League team		-0.217	-0.215
		(0.132)	(0.133)
Team win percentage (previous season)	-0.533**	-0.710**	-0.903**
	(0.141)	(0.116)	(0.142)
Coach's experience in the current team	0.007	0.010+	0.010+
	(0.007)	(0.005)	(0.005)
Number of learners in the team	-0.016	-0.012	-0.005
	(0.011)	(0.009)	(0.010)
Number of competitors in the team	-0.018	-0.008	0.009
	(0.015)	(0.012)	(0.014)
Team salary	0.046	0.335**	0.295**
	(0.095)	(0.077)	(0.080)
Number of observations	2,919	2,919	2,919
Number of clusters	1,047	1,047	1,047
R-squared	0.024	0.381	0.382
Log-likelihood	-3672	-3008	-3005

Notes: ** p<0.01, * p<0.05, + p<0.1; All models include team and season fixed effects; Standard errors in parentheses and clustered at player level.

Table 7: Change in performance of junior/senior competitors in the presence of stars

OLS model; VORP-based measure of performance	**1**	**2**	**3**	**4**	**5**	**6**
DV: Change in junior/senior competitor's performance	**Junior Comp.**	**Junior Comp.**	**Junior Comp.**	**Senior Comp.**	**Senior Comp.**	**Senior Comp.**
Number of stars in the team	0.102			-0.011		
	(0.068)			(0.046)		
Number of junior stars in the team		-0.070			0.084	
		(0.065)			(0.054)	
Number of senior stars in the team			0.152*			-0.070+
			(0.061)			(0.040)
Change in playing time over last season	0.097**	0.098**	0.096**	0.116**	0.116**	0.117**
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.008)
Time played in the team in current season	0.044**	0.043**	0.045**	0.021**	0.021**	0.021**
	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)
Change in player's salary	-0.059	-0.074	-0.061	0.014	0.016	0.004
	(0.073)	(0.074)	(0.073)	(0.095)	(0.094)	(0.094)
Player's league experience	-0.005	-0.007	-0.006	-0.008	-0.008	-0.008
	(0.035)	(0.035)	(0.035)	(0.012)	(0.011)	(0.011)
Player's experience in the current team	0.019	0.016	0.014	-0.016	-0.014	-0.016
	(0.032)	(0.033)	(0.032)	(0.012)	(0.011)	(0.012)
Player is a free agent	-0.094	-0.108	-0.103	0.074	0.079	0.068
	(0.093)	(0.093)	(0.093)	(0.075)	(0.075)	(0.075)
Best defensive player nomination	0.020	0.005	0.013	-0.153	-0.157	-0.161
	(0.164)	(0.161)	(0.160)	(0.142)	(0.143)	(0.143)
Best sixth man nomination	-0.140	-0.149	-0.140	-0.178	-0.176	-0.170
	(0.114)	(0.115)	(0.113)	(0.126)	(0.126)	(0.125)
Most improved player nomination	-0.236*	-0.234*	-0.237*	-0.215	-0.222	-0.211
	(0.096)	(0.097)	(0.097)	(0.158)	(0.157)	(0.157)
Most valuable player nomination	0.032	0.006	0.008	0.004	0.002	0.005
	(0.283)	(0.279)	(0.285)	(0.137)	(0.138)	(0.139)
Best rookie nomination	0.081	0.084	0.078			
	(0.182)	(0.178)	(0.179)			
Nomination to All-Defensive team	-0.368	-0.342	-0.436	0.058	0.038	0.070
	(0.272)	(0.264)	(0.278)	(0.187)	(0.189)	(0.184)
Nomination to All-Rookie team	0.132	0.138	0.133			
	(0.199)	(0.196)	(0.195)			
Nomination to All-League team	1.941**	2.003**	1.958**	0.839*	0.830*	0.826*
	(0.347)	(0.338)	(0.344)	(0.402)	(0.421)	(0.419)
Team win percentage (previous season)	-1.465*	-0.969+	-1.454**	-0.646	-0.763*	-0.480
	(0.640)	(0.507)	(0.551)	(0.412)	(0.366)	(0.386)
Coach's experience in the current team	0.017	0.017	0.018	0.015	0.015	0.014
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Number of learners in the team	0.012	-0.007	0.011	-0.008	-0.001	-0.013
	(0.026)	(0.027)	(0.026)	(0.019)	(0.018)	(0.018)
Number of competitors in the team	0.100**	0.062	0.101**	-0.044	-0.036	-0.060*
	(0.037)	(0.038)	(0.036)	(0.030)	(0.026)	(0.028)
Team salary	0.076	0.113	0.013	0.315	0.329	0.381
	(0.229)	(0.236)	(0.232)	(0.236)	(0.232)	(0.236)
Number of observations	605	605	605	634	634	634
Number of clusters	371	371	371	312	312	312
R-squared	0.570	0.569	0.573	0.636	0.637	0.637
Log-likelihood	-712.8	-713.6	-711.0	-649.3	-648.1	-648.1

Notes: ** p<0.01, * p<0.05, + p<0.1; Rookie-related variables dropped because senior players are not eligible for these awards; All models include team and season fixed effects; Standard errors in parentheses and clustered at player level.

Table 8: Descriptive statistics and correlation matrix of variables to estimate team performance

S No.	Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1	Team win percentage (current season)	0.501	0.156	0.106	0.890	1							
2	Ratio of (Learners + Junior competitors) to (Learners + All competitors)	0.868	0.120	0.375	1	-0.351	1						
3	Team salary	26.065	9.061	6.573	57.683	0.239	-0.281	1					
4	Number of stars in the team	1.133	0.996	0	4	0.604	-0.203	0.237	1				
5	Number of players on the team roster	15.288	1.733	11	22	-0.373	0.076	0.123	-0.220	1			
6	Team tenure of stars	3.085	2.883	0	18	0.440	-0.206	0.342	0.580	-0.159	1		
7	Team tenure of learners + junior competitors	2.440	0.661	1.167	6	0.166	-0.017	0.247	0.084	-0.144	0.176	1	
8	Team tenure of senior competitors	2.297	2.315	0	13	0.226	-0.563	0.285	0.110	-0.014	0.186	0.111	1
9	Number of players on All-Defensive team	0.176	0.428	0	3	0.363	-0.211	0.159	0.396	-0.072	0.333	0.048	0.082
10	Number of players on All-Rookie team	0.177	0.406	0	2	-0.159	0.204	-0.141	-0.170	0.072	-0.147	-0.075	-0.148
11	Number of players on All-League team	0.171	0.409	0	2	0.382	-0.108	0.164	0.433	-0.054	0.320	0.060	0.058
12	Number of best defensive player nominations	0.502	0.756	0	3	0.351	-0.226	0.376	0.415	-0.015	0.353	0.166	0.128
13	Number of most valuable player nominations	0.453	0.688	0	3	0.468	-0.274	0.337	0.531	-0.097	0.462	0.142	0.194
14	Number of best sixth man nominations	0.409	0.636	0	3	0.187	-0.155	0.291	0.153	-0.037	0.179	0.150	0.144
15	Number of most improved player nominations	0.748	0.862	0	4	0.108	-0.003	0.232	0.164	-0.054	0.114	0.083	0.017
16	Number of best rookie player nominations	0.213	0.445	0	2	-0.119	0.173	0.000	-0.169	0.065	-0.122	-0.041	-0.132
17	Attendance to stadium capacity ratio (season)	0.896	0.109	0.469	1.119	0.510	-0.281	0.281	0.392	-0.141	0.303	0.064	0.225
18	Coach's experience in the current team	3.148	3.074	1	21	0.287	-0.135	0.028	0.205	-0.069	0.251	0.131	0.127
19	Coach change during the season	0.129	0.335	0	1	-0.257	0.029	0.023	-0.060	0.064	-0.043	-0.041	-0.016
20	Team win percentage (previous season)	0.500	0.158	0.106	0.890	0.656	-0.444	0.296	0.671	-0.198	0.550	0.144	0.322

S No	Variables	9	10	11	12	13	14	15	16	17	18	19	20
9	Number of players on All-Defensive team	1											
10	Number of players on All-Rookie team	-0.131	1										
11	Number of players on All-League team	0.471	-0.109	1									
12	Number of best defensive player nominations	0.457	-0.070	0.374	1								
13	Number of most valuable player nominations	0.406	-0.120	0.495	0.452	1							
14	Number of best sixth man nominations	0.074	0.017	0.063	0.218	0.239	1						
15	Number of most improved player nominations	0.005	-0.025	0.014	0.199	0.174	0.291	1					
16	Number of best rookie player nominations	-0.139	0.696	-0.125	-0.012	-0.117	0.061	0.065	1				
17	Attendance to stadium capacity ratio (season)	0.213	-0.051	0.291	0.248	0.380	0.208	0.108	-0.044	1			
18	Coach's experience in the current team	0.178	-0.001	0.233	0.136	0.229	0.098	0.034	-0.051	0.186	1		
19	Coach change during the season	-0.072	0.024	-0.001	-0.039	-0.021	-0.035	0.013	0.037	-0.122	-0.118	1	
20	Team win percentage (previous season)	0.422	-0.253	0.456	0.435	0.561	0.263	0.118	-0.255	0.472	0.288	-0.068	1

Notes: N = 729; 'All competitors' include both junior and senior competitors; Correlations greater than |0.08| are significant at the 0.05 level or lower; Variable 3 (team salary) is adjusted for CPI and rescaled using logarithmic values.

Table 9: Estimating team performance as a function of learners and competitors

OLS Model; VORP-based measure of player performance	1	2	3	4
DV: Team win percentage (current season)	**Win percentage**	**Win percentage**	**Win percentage**	**Win percentage**
Ratio of (L+JC)/(L+C) non-stars				0.683*
				(0.328)
Square of ratio of (L+JC)/(L+C) non-stars				-0.466*
				(0.203)
Team salary			0.004**	0.004**
			(0.001)	(0.001)
Number of stars in the team			0.032**	0.034**
			(0.005)	(0.005)
Number of players on the team roster			-0.024**	-0.023**
			(0.002)	(0.002)
Team tenure of stars			-0.001	-0.001
			(0.001)	(0.001)
Team tenure of learners + junior competitors			0.009	0.009
			(0.007)	(0.007)
Team tenure of senior competitors			0.001	-0.003
			(0.002)	(0.002)
Number of players on All-Defensive team		0.019	0.015	0.014
		(0.013)	(0.011)	(0.011)
Number of players on All-Rookie team		-0.034**	-0.025*	-0.024*
		(0.012)	(0.011)	(0.011)
Number of players on All-League team		0.017	0.016	0.017
		(0.014)	(0.012)	(0.012)
Number of best defensive player nominations		0.009	0.003	0.002
		(0.007)	(0.008)	(0.007)
Number of most valuable player nominations		0.015	0.002	0.002
		(0.010)	(0.007)	(0.007)
Number of best sixth man nominations		-0.002	-0.002	-0.003
		(0.006)	(0.006)	(0.006)
Number of most improved player nominations		0.008	0.003	0.004
		(0.005)	(0.005)	(0.005)
Number of best rookie player nominations		0.039**	0.040**	0.040**
		(0.011)	(0.009)	(0.009)
Attendance to stadium capacity ratio (season)	0.478**	0.438**	0.372**	0.354**
	(0.055)	(0.060)	(0.053)	(0.052)
Coach's experience in the current team	0.001	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Coach change during the season	-0.088**	-0.090**	-0.084**	-0.085**
	(0.011)	(0.010)	(0.010)	(0.010)
Team win percentage (previous season)	0.430**	0.349**	0.177**	0.166**
	(0.034)	(0.044)	(0.045)	(0.043)
Number of observations	729	729	729	729
Number of clusters	30	30	30	30
R-squared	0.557	0.575	0.665	0.669
Log-likelihood	616.8	632.3	719.0	722.8

Notes: ** $p<0.01$, * $p<0.05$, + $p<0.1$; 'L' represents number of learners, 'JC' represents number of junior competitors, and 'C' represents number of junior and senior competitors; All models include team and season fixed effects; Standard errors in parentheses and clustered at team level.

Table 10: Robustness tests for the inverted U-shaped relation using game-level team performance

OLS Model; VORP-based measure of player performance DV: Win-loss dummy (Win=1; Loss=0)	1 Inverted U-shaped relation	2 L&M test for inverse U-shape	3 Checking S-curve
Ratio of (L+JC)/(L+C) non-stars	0.703**		-0.977
	(0.243)		(1.137)
Square of ratio of (L+JC)/(L+C) non-stars	-0.493**		1.759
	(0.151)		(1.556)
Cube of ratio of (L+JC)/(L+C) non-stars			-0.978
			(0.691)
Slope at lower bound		0.334**	
		(0.008)	
Slope at upper bound		-0.282**	
		(0.000)	
Number of observations	58,614	58,614	58,614
R-squared	0.129		0.129
Log-likelihood	-38488		-38487
Overall p-value of inverse U-shape		(0.008)	

Notes: ** p<0.01, * p<0.05, + p<0.1; Number of clusters = 30; 'L' is the number of learners, 'JC' is the number of junior competitors, and 'C' is the number of junior and senior competitors; Results for control variables not reported; Models include team, opponent, and season fixed effects; Standard errors are in parentheses (except for Model 2) and are clustered at team level. In Model 2, the inverse U-shaped relation is tested using Fieller interval (Lind & Mehlum, 2010) and parentheses report the p-values of point estimates and overall shape.

Table 11: Robustness tests for the inverted U-shaped relation using alternate ratio

OLS Model; VORP-based measure of player performance DV: Team win percentage (current season) in Model 1; Win-loss dummy in Models 2-4.	1 Inverted U-shaped relation	2 Inverted U-shaped relation	3 L&M test for inverse U-shape	4 Checking S-curve
Ratio of L/(L+C) non-stars	0.378*	0.277+		0.782
	(0.167)	(0.137)		(0.701)
Square of ratio of L/(L+C) non-stars	-0.341**	-0.281**		-1.051
	(0.119)	(0.097)		(1.108)
Cube of ratio of L/(L+C) non-stars				0.375
				(0.554)
Slope at lower bound			0.153+	
			(0.059)	
Slope at upper bound			-0.284**	
			(0.000)	
Number of observations	729	58,614	58,614	58,614
R-squared	0.674	0.130		0.130
Log-likelihood	728.4	-38474		-38473
Overall p-value of inverse U-shape			(0.059)	

Notes: ** p<0.01, * p<0.05, + p<0.1; Number of clusters = 30; 'L' is the number of learners; 'C' is the number of junior and senior competitors; Results for control variables not reported; Models include team and season fixed effects; Standard errors are in parentheses (except for Model 3) and are clustered at team level. In Model 3, the inverse U-shaped relation is tested using Fieller interval (Lind & Mehlum, 2010) and parentheses report the p-values of point estimates and overall shape.

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