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Resource allocation and the production of star performers

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ABSTRACT

How can managers allocate resources among workers in a cohort to increase the proportion of star performers? To answer this question, we derived four competing hypotheses based on the resource-based theory: (H1) Use potential-based allocation (i.e. allocating resources based on workers' potential) in early and later years on the job; (H2) Use both potential-based allocation and performance-based allocation (i.e. allocating resources based on workers' actual performance on the job) in early and later years; (H3) Use potential-based allocation in early years, but use performance-based allocation in later years; and (H4) Use performance-based allocation, but not potential-based allocation, in early and later years. Using data from 280 Major League Baseball (MLB) cohorts encompassing 17,499 unique players, our results offered support for H3 by showing that potential-based allocation used in early years on the job (i.e. years 1–2) predicts a greater proportion of stars in cohorts, whereas performance-based allocation does so when used in later years (i.e. years 3–6). Thus, rather than treating potential- and performance-based allocation as rival mechanisms as often done in prior work, our main contribution is to show that potential- and performance-based allocation are different parts of a more comprehensive framework. As another contribution, our results supported H3's rationale: As performance becomes more relevant compared to potential over time, managers become willing to allocate resources more closely based on performance in later years. The same rationale helps explain why some studies in the star performance literature supported using potential-based allocation while others supported using performance-based allocation. From a practical significance perspective, we describe how using potential- and performance-based allocation during different times based on our findings can translate to having more stars of higher quality (e.g. an organization having five star performers rather than two).

KEYWORDS
Star performers; allocation; resources; opportunity; cohorts

Q2

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Workers in a cohort—who started their tenure in an organization or industry around the same time despite possibly spanning across different managers or units—receive and often compete for valuable yet scarce resources that are useful for becoming star performers (Downes & Lee, 2023; Dries, 2013; Gallardo-Gallardo et al., 2013; Marshall et al., 2024; Silzer & Church, 2009, 2010). For example, Michel (2011) used data on cohorts of investment bankers, where each cohort consisted of those who started working at the same bank as entry-level associates around the same year but spanned across different teams, projects, or clients served. Given this, it is important to understand the following research question: *How can managers allocate resources among workers in a cohort to increase the proportion of star performers?* The human resource management (HRM) field would benefit from examining this question because stars are workers who generate disproportionately larger amounts of output compared to peers (O'Boyle & Aguinis, 2012). Due to their disproportionate output, stars also often have an outsized effect on organizations and even societies (Asgari et al., 2021; Joo et al., 2022; Minbaeva & Collings, 2013). Though stars can sometimes exert negative effects including negative stock-price movements (Groysberg & Lee, 2009) and reduced group effectiveness (Zhou et al., 2025), stars have been known to help create economic growth (Zucker & Darby, 1996), improve firm revenue (Han & Ravid, 2020), increase the odds of firm survival (Bedeian & Armenakis, 1998), and contribute to peers' performance (Ammann et al., 2016), among other positive effects. To the extent that stars are beneficial in certain contexts, managers would be interested in knowing how to allocate resources to achieve a greater proportion of stars.

To answer our research question, we used the resource-based theory (RBT) to derive four competing hypotheses on how different ways of allocating resources per cohort predict the proportion of stars: (H1) Use potential-based allocation (i.e. allocating resources based on based on workers' potential) in early and later years on the job, where potential refers to workers' predicted performance in a future job/position that they have not yet started; (H2) Use both potential-based allocation (as previously defined) and performance-based allocation (i.e. allocating resources based on workers' actual performance on the job rather than predicted performance before starting the job) in early and later years; (H3) Use potential-based allocation in early years, but use performance-based allocation in later years; and (H4) Use performance-based allocation, but not potential-based allocation, in early and later years. These hypotheses are different combinations of whether and how two independent variables (i.e. potential- and performance-based allocation) predict the dependent variable (i.e. the proportion of stars).

In terms of the level of analysis, it is critical to note that the independent and dependent variables are at the *cohort* level because workers in the same cohort have a common baseline (i.e. starting point), which allows for a more accurate test of our four hypotheses (i.e. better isolation of the degree to which potential- and/or performance-based allocation predict the proportion of stars). A non-cohort unit such as a team often consists of individuals with widely varying starting points, including those new to a job and those who started decades ago. Individuals with an earlier head start are more likely to be counted as stars simply because they had more time to receive resources, regardless of potential- or performance-based allocation. One possible trade-off of our cohort level focus is that our findings (i.e. on what a manager can do to develop star performers among workers) may not apply to the individual level of analysis (i.e. on what an individual can do to develop oneself into a star), as conclusions from one level of analysis do not necessarily apply to another level of analysis (Dalal et al., 2014). Nonetheless, we chose to conduct our study at the cohort level because it accounts for the reality that resources are often limited and cannot be obtained in large amounts by all individuals (Huselid & Becker, 2011). In contrast, the individual level of analysis does not because it focuses on the perspective of an individual worker rather than that of a manager dealing with numerous workers (e.g. in a cohort) who may benefit from and even compete for scarce resources that the manager allocates.

Empirically, we used data from 280 Major League Baseball (MLB) cohorts encompassing 17,499 unique players. Based on the 280 cohorts, we operationalized our independent and dependent variables per cohort. As a result, each data point in our regression models is a cohort rather than a team or individual. Results showed that potential-based allocation used in the early years on the job (i.e. years 1–2) predicts a greater proportion of stars in cohorts. In contrast, performance-based allocation does so when used in later years (i.e. years 3–6). These findings offer empirical support for H3 among our four competing hypotheses. In addition, we conducted additional analyses and found empirical support for the theoretical rationale underlying H3: Performance becomes more relevant compared to potential over time, such that managers become willing to allocate resources more closely based on performance in later years.

Our results offer several contributions to theory in the star performance literature. First, we show that potential- and performance-based allocation are not rival allocation mechanisms (as often portrayed in prior studies), but rather different parts of a more comprehensive framework. This is because we found that although both potential- and performance-based allocation predict a greater proportion of stars, they do so in different time frames (early versus later years on the job, respectively). Thus, our study helps reconcile and integrate past research debating whether potential- or performance-based allocation is the better way to allocate resources. Second, our additional results offer an explanation for *why* potential-based allocation used in early years on the job predicts the proportion of stars in cohorts, while performance-based allocation does so when used in later years: As performance becomes more relevant compared to potential over time, managers become willing to allocate resources more closely based on performance in later years. This explanation helps account for why some studies supported using potential-based allocation while others supported using performance-based allocation. That is, studies finding greater support for using potential-based allocation may have focused on early periods in workers' performance, which our study suggests is when performance is less relevant. In contrast, studies finding greater support for using performance-based allocation may have more heavily incorporated later periods in workers' performance, which our study suggests is when performance becomes more relevant such that managers are more willing to allocate resources closely based on performance.

As another contribution to theory, our study expands the role of the RBT in explaining phenomena in the star performance literature. This is because we show how the RBT can help explain not only consequences but also antecedents regarding star performers. Specifically, research in the star performance literature has thus far used RBT logic to explain the value or consequences of having star performers. Departing from such focus on explaining the consequences of stars, our study demonstrates how the RBT logic can be used to explain antecedent mechanisms leading to more star performers.

Theory and hypotheses

In this section, we elaborate on four competing hypotheses regarding whether and how potential- and performance-based allocation predict the proportion of stars in cohorts. Our overarching theoretical framework begins with the RBT in that different variations of the theory offer rationale for each of our four hypotheses. According to the RBT, putting together a set of valuable, rare, inimitable, and non-substitutable (VRIN) resources is essential for a firm to achieve a sustained competitive advantage (Barney, 1991). The RBT is a logical starting point for our theorizing given that our study is concerned with how managers can allocate resources (including VRIN resources such as opportunities to perform) to increase the proportion of star performers, who are often seen as sources of a sustained competitive advantage (e.g. Aguinis & O'Boyle, 2014).

An aspect of the RBT that is particularly relevant is the implicit assumption that the firm's environment is relatively stable rather than being subject to dramatic or constant changes (D'Aveni et al., 2010). Such stability makes it important for a firm to bundle a set of consistently VRIN resources to achieve a sustained (not temporary) competitive advantage. In other words, combining stable VRIN resources (or, more precisely, resources that are stable in terms of VRIN) leads to a stable competitive advantage.

Applied to the context of workers, a relatively stable firm environment means that managers should provide more resources to individual workers with more consistently VRIN characteristics to produce a greater proportion of star performers in cohorts. Our study captures consistently VRIN characteristics *via* the notion of potential, defined as workers' predicted performance in a future job or position that they have not yet started (Gallardo-Gallardo et al., 2013; Silzer & Church, 2009; Tormala et al., 2012). This is because potential incorporates a wide range of individual characteristics to emulate the future work environment's complexity and constraints (Cascio & Aguinis, 2008). For example, organizations have defined and assessed employees' potential to perform general leadership roles, start a business, manage product development, or conduct innovative research (Silzer & Church, 2009). To the extent that potential is comprehensive and predictive of the future, potential can be thought of as a set of characteristics that are consistently VRIN across various contexts. Hence, as one way to bundle consistently VRIN resources, managers can allocate resources based on workers' potential to produce a greater proportion of stars in cohorts.

In turn, allocating resources based on workers' potential may help increase the proportion of stars by setting off a positive feedback loop, in which workers with greater potential obtain more resources that help them better realize their potential (i.e. by improving performance on the job). These workers will then receive larger amounts of resources or continue to receive large amounts of resources. To the extent that higher-potential workers become higher-performers in a positive feedback loop, potential-based allocation can become more positively correlated with performance-based allocation over time (though still distinct from each other), to the effect of predicting a greater proportion of stars. In summary, the above RBT logic provides theoretical support for the first hypothesis, which states:

H1: Potential-based allocation, used in early and later years on the job, predicts a greater proportion of stars in cohorts.

But what if, contrary to the RBT's implicit assumption, firm environments are largely *un*stable and are subject to dramatic or constant changes? Studies examining and critiquing this aspect of the RBT have uncovered evidence suggesting that competitive advantages are becoming less sustained and more temporary over time (Ruefli & Wiggins, 2003; Thomas & D'Aveni, 2009; Wiggins & Ruefli, 2005). What looks like a firm maintaining a sustained competitive advantage may instead be a series of temporary advantages, one after another. The increasingly temporary nature of competitive advantages can be attributed to several factors such as technological change, globalization, aggressive competitive behavior, and/or industry convergence. Whatever the precise reasons for increasingly temporary competitive advantages, such instability makes it less important for a firm to bundle a set of consistently VRIN resources to achieve a sustained competitive advantage. What is more important is to bundle resources that are VRIN at the given time or context to pursue one temporary advantage after another.

In the context of workers, an unstable firm environment means that the future work environment emulated by potential is subject to dramatic or constant changes. For example, to the extent that competitors change or adjust their strategies, individual characteristics such as knowledge, skills, and abilities encompassed by potential that were well-suited for responding to competitors' original strategies may become less useful for dealing with competitors' new strategies. If so, potential would be a less effective basis for allocating resources among workers. To more successfully produce a greater proportion of star performers, managers should provide more resources to workers showing higher performance than others at the moment (i.e. an indicator of individual characteristics that are VRIN at the given time or context), even if the currently high-performing workers were not initially assessed as being high potential. Examples of current performance include results produced on the job, such as number of products assembled, new clients secured, and revenue generated (Aguinis et al., 2016; Joo et al., 2017).

However, we do not mean to imply that a sustained competitive advantage is non-existent or negligible in a largely unstable firm environment. The issue of sustained and temporary competitive advantage is a matter of degree, and firms can have both sustained competitive advantages (e.g. *via* oligopolistic behaviors) and temporary competitive advantages (e.g. *via* innovation). The importance of both sustained and temporary competitive advantages suggests that managers should allocate resources based on both potential (an indicator of at least somewhat consistently VRIN characteristics) and performance on the job (an indicator of characteristics that are VRIN at the given time or context). This relaxed RBT rationale provides theoretical support for the second hypothesis, which states:

> *H2:* Both potential- and performance-based allocation, used in early and later years on the job, predict a greater proportion of stars in cohorts.

A further relaxation of RBT's implicit assumption about a stable firm environment leads to additional competing hypotheses on how to allocate resources to produce a greater proportion of stars. Specifically, firm environments may have developed into a further intensified level of instability described as 'hypercompetitive' (D'Aveni et al., 2010; James et al., 2023). In hypercompetitive environments, competitors are not merely working hard to be the best versions of themselves but are deliberately and aggressively working to destroy the competitive advantages of top performers in an industry (Schumpeter, 1942). Top performers, in turn, must continuously strive to replace their own VRIN resources in an effort to renew their competitive advantages. If a top-performing firm fails to continuously renew its competitive advantage, the firm's existing competitive advantage may soon be destroyed by competitors, causing it to lose its top-performer position.

Given the key role of aggressive competitive behaviors in making resources obsolete and creating a hypercompetitive environment, hypercompetition is not limited to high-tech industries but instead occurs throughout many industries—though hypercompetition seems to be more heavily present in high-tech than other industries (Wiggins & Ruefli, 2005). For example, the social media industry can be thought of as being hypercompetitive given its history of new entrants successfully and quickly replacing incumbents (e.g. in the United States, after Myspace was mostly replaced by Facebook and Instagram, TikTok became the dominant social media platform among teenagers and young adults, but most recently TikTok might lose its dominant position if it were to be permanently banned). Automobile manufacturers can also be considered a hypercompetitive industry currently characterized by not only incumbents with a long history but also newcomers trying to overthrow each other in the emerging market for electric vehicles and hybrids (e.g. Tesla's dominant status in the electric vehicle market is being increasingly challenged by other automakers as they introduce their own electric vehicles which are often cheaper, contributing to Telsa's significant price cuts in the years 2023–2024).

Applied to the context of workers, a hypercompetitive environment suggests that individual potential as a basis for allocating resources may be useful in the early years on the job (e.g. first two to three years), to the extent that potential seeks to emulate the future work environment as previously described. But the same potential might soon become obsolete as players compete with one another and make each other's current skillsets and strategies obsolete. In the least, the importance of potential may stay constant rather than become obsolete while other factors become more relevant over time. For example, a high-potential worker who also once enjoyed high performance may soon be surpassed by a worker who was initially assessed as low or average potential but later manages to achieve 'rapid improvement in performance' (Minbashian & Luppino, 2014, p. 903). Thus, in later years (e.g. third year and beyond), an increasingly superior basis for allocating resources may be individual performance on the job, as current performance more closely captures skills and strategies that are advantageous at the time than potential does. If so, managers would be willing to allocate resources more closely based on performance in later years and, therefore, performance-based allocation will predict a greater proportion of stars. This hypercompetition-focused RBT logic offers theoretical support for our third hypothesis, which states:

> *H3:* Potential-based allocation used in early years on the job predicts a greater proportion of stars in cohorts, while performance-based allocation does so when used in later years.

A hypercompetition-focused RBT perspective may go as far as to suggest an intensity of competition extreme enough to make potential immediately obsolete as a useful basis for allocating resources once on the job. If so, between potential and performance on the job, only the latter would be a valid basis for allocating resources to produce a greater proportion of star performers in cohorts.

Extreme hypercompetition also implies less room for errors or underperformance because competitors can quickly exploit errors and underperformance. In this hypercompetitive environment, individual workers might experience disproportionate stress from committing errors or underperformance. Those who are most likely subject to such stress are high-potential individuals who receive larger amounts of resources related to performing more on the job (e.g. opportunities to perform), because allocating large amounts of such resources to higher-potential workers who do not perform immediately well can inadvertently and repeatedly expose them to experiencing underperformance. In turn, inconsistencies between being considered higher potential and repeated sub-par performance can create excessive chronic stress, leading to fatigue, burnout, or health issues (Chida & Hamer, 2008; Segerstrom & Miller, 2004; Taleb, 2012), which are detrimental to becoming a star performer.

Indeed, practitioner reports hint that many higher-potential individuals do not perform well immediately on the job. A survey of managers across 59 organizations, 15 industries, and 29 countries found that just 29% of high performers at the time were also deemed high-potential (Corporate Leadership Council, 2005). Similarly, managers in companies such as Johnson & Johnson have explicitly distinguished potential from performance (Fulmer, 2001). To the extent that potential and actual performance are different, potential-based allocation may translate to higher-potential individuals experiencing underperformance and suffering from disadvantages such as stress, reducing the usefulness of potential as a basis for allocating resources. Hence, we offer the following fourth hypothesis:

> *H4:* Performance-based allocation, used in early and later years on the job, predicts a greater proportion of stars in cohorts while potential-based allocation does not.

Method

Data collection

We collected regular season data on MLB players from sports-reference.com, baseballprospectus.com, and prosportstransactions.com. As a result, our dataset contained 280 cohorts (i.e. 140 batter and 140 pitcher cohorts), encompassing 17,499 unique players and covering the years 1871 to 2019. Players in each cohort have a common baseline: They played their first MLB game in the same regular season (e.g. the 1990 batter cohort consists of batters who played their first MLB game in 1990). Because we used publicly available archival data, our study was granted exempt status from the Institutional Review Board at the authors' affiliated institutions at the time (protocol #1411707694).

This sports dataset is well-suited for our study because we seek to predict the proportion of star performers across cohorts and, therefore, choosing an empirical context that allows for stars to emerge in the first place is vital. The MLB satisfies this criterion as it is the highest-level league in baseball and consists of the best of the best—a pool of individuals from which stars are likely to emerge. Another advantage of using MLB is that it reflects an unstable or highly competitive environment where an individual's initially assessed potential (based on certain characteristics) may become less relevant for future performance while current performance becomes more so. For example, skills and strategies initially considered effective at lower-level leagues (e.g. minor leagues) or in past MLB seasons may become increasingly obsolete in future MLB seasons. The presence of such instability or competition allows us to empirically examine our four competing hypotheses, which vary in the degree to which potential may become a less effective basis for allocating resources among workers.

Data preparation

Next, we sought to keep only individual players occupying strategic positions (i.e. positions with close proximity to an organization's core competence) while removing players occupying non-strategic positions (i.e. positions with low proximity to an organization's core competence) (Aguinis & O'Boyle, 2014). This is because individuals in strategic positions have a better chance of significantly contributing to their organizations, giving those individuals a realistic chance of becoming star performers over time. In contrast, those in non-strategic positions are far removed from the core competences of their organizations and have, at best, a minimal chance of making such a significant contribution and becoming star performers. For example, full-time positions can generally be considered strategic, whereas temporary hires or interns can be considered non-strategic. Indeed, it is unlikely that temporary workers or interns whose futures with their organizations are currently uncertain would nonetheless receive major developmental resources/investments from their organizations in the first place.

To remove players in non-strategic positions, we excluded batters with plate appearances or at-bats fewer than 10 and pitchers with innings pitched fewer than 10. We chose 10 as the threshold because this number minimally exceeds the total number of innings played in a single baseball game, which consists of nine innings. Given such, it is difficult to consider a player who has only played a combined total of one game or less as having occupied a strategic position that is capable of significantly contributing to one's organization. Those who played a total of one game or less are more likely to represent non-strategic positions (e.g. created temporarily for a player from a lower-level league to fill in for a regular MLB player recovering from an injury at the time). In other words, players who played a total of one game or less are analogous to temporary hires or interns who worked at a company for one project or one (busy) time of the year. In short, by retaining players with at least 10 innings worth of game time while removing other players, we limited our analyses to only those in strategic positions with realistic chances of making significant contributions and thus becoming star performers. Enforcing this threshold also has the added methodological benefit of removing players who often have extreme values for their performance statistics—likely due to purely statistical fluctuations allowed by low denominator values (e.g. a player is more likely to generate a very high slugging percentage if he had a very small number of at-bats, regardless of the player's true performance).

After completing the above data preparation procedures, there were 90 cohorts available for potential-based allocation, consisting of 45 batter and 45 pitcher cohorts (containing 3,299 batters and 2,659 pitchers, respectively). The data for performance-based allocation included 268 cohorts made of 138 batter and 130 pitcher cohorts (containing 7,442 batters and 4,343 pitchers, respectively). The number of cohorts for potential-based allocation was noticeably smaller due to limited data on players' potential. Given our choice to operationalize potential as overall pick numbers determined during new player drafts (as described in more detail later in 'Cohort-Level Predictors'), the earliest new player draft in MLB did not occur until 1965. In contrast, performance data are available as early as 1871—hence, the number of cohorts for performance-based allocation is greater.

Cohort-level dependent variable: proportion of star performers

The dependent variable for all four competing hypotheses is the proportion of stars produced in a cohort of workers. To operationalize our cohort-level dependent variable, we first conducted an intermediate step at the individual level of analysis by identifying each player's cumulative output in terms of wins-above-replacement (WAR). Cumulative WAR quantifies the net total number of wins that a player added to his team(s) over his entire MLB career (Swaab et al., 2014). For example, Hank Aaron accumulated 142.6 WAR over 23 seasons in MLB, indicating 142.6 wins contributed to his teams during his MLB career. To attribute the number of team wins to a player, WAR considers all measurable dimensions of a player's performance rather than just one or few dimensions (e.g. number of homeruns). As a result, the use of WAR prevents us from overrating players who excel at one or few performance dimensions, as well as from underrating well-rounded players who do not particularly excel at any one dimension (Darowski, 2011). Cumulative WAR can also be negative, which means that a player ultimately costs his team(s) a certain number of wins.

Next, we identified the distribution of cumulative individual output per cohort of players. The number of players in a cohort did not drop as players moved back down to lower leagues, retired, or otherwise exited MLB because we focused on each player's cumulative output rather than output generated per limited period. Thus, cohorts do not vary from one another based on attrition. Further, a cohort's distribution refers to its final season, or the year when all players in the cohort accumulated output for the last time (i.e. after which no change occurred to anyone's output). The final season was the 27th season for every cohort because, in our dataset, 27 was the greatest number of MLB seasons that a player ever played (held by Cap Anson and Nolan Ryan).

We then measured each distribution's right-tail heaviness by calculating its power law parameter alpha (α) (Aguinis et al., 2018; Clauset et al., 2009; Joo et al., 2017):

$$p(x) \propto x^{-\alpha}, \tag{1}$$

where x refers to a player's cumulative output; p (x) is the expected frequency (i.e. likelihood) of observing a player with x amount of cumulative output; and exponent α quantifies the distribution's right-tail heaviness. The smaller and closer power law's α to 1.0, the heavier the distribution's right tail, indicating a greater proportion of stars in the cohort.

An advantage of the power law α is that it does not artificially dichotomize individuals into stars versus non-stars. In a power law distribution of cumulative individual output, those closer to the right end of the distribution are more highly-performing stars. Another advantage is that power law α quantifies the heaviness of a distribution's right tail, where the highest performers exist. Thus, power law's α values vary across cohorts due to the strength of higher performers per cohort, not the weakness of lower performers. In fact, the R code we used removes the lowest performers per cohort by imposing 'a lower bound' (Clauset et al., 2009, p. 663).

Cohort-level predictors

Potential-based allocation

To operationalize potential-based allocation, we first conducted an intermediate step at the individual level by specifying resources as opportunities to perform. Workers need opportunities to perform to generate output, and those opportunities are often limited (Aguinis et al., 2016; Vancouver et al., 2016). Examples of opportunities to perform include projects for knowledge workers, sales territory for salespeople, patients for medical doctors, minutes played for athletes, and challenging tasks for employees in general (De Pater et al., 2009; DeRue & Wellman, 2009; Netessine & Yakubovich, 2012; Pasternack et al., 2016). In our empirical context (i.e. MLB), we measured opportunities to perform by using number of plate appearances for batters and number of innings pitched for pitchers.

The next intermediate step at the individual level was to measure potential as overall pick numbers (i.e. the order in which players were picked in new player drafts before playing in MLB), where lower overall pick numbers denote higher potential. We used overall pick number because it reflects potential-based allocation's early-career focus, given that potential refers to workers' predicted performance in a future job or position that they have not yet started, as previously mentioned. Overall pick number has an early-career focus because it is decided in new player drafts before a player plays his first MLB game, which typically occurs one or more years after his draft. To determine players' overall pick numbers in drafts, teams in MLB consider a wide variety of early-career indicators such as their counterproductive work behaviors (CWBs) (Cotterill, 2017), organizational citizenship behaviors (Pleskoff, 2012), and pre-draft Magnetic Resonance Imaging scans (Ley, 2016).

Another reason for measuring potential as overall pick numbers is their reliance on subjective assessments, which generally differ from and thus are not interchangeable with objective performance (Bommer et al., 1995; Jaramillo et al., 2005). The reliance on subjective assessments is embedded within the process of determining a worker's potential because organizations quantify a worker's potential by identifying multiple variables and aggregating the total information, both of which involve judgment calls (e.g. how to weigh the multiple types of information). For example, some firms aggregate 'immediate manager's recommendation,' 'corporate-level assessments,' and other sources to judge employees' potential (Silzer & Church, 2009, p. 383). Given such, overall pick number closely reflects the use of subjective assessments because overall pick number aggregates multiple evaluators' multi-dimensional assessments into a single number, and this aggregation ultimately involves judgment calls regarding how to aggregate the total information (e.g. how much weight to assign to each evaluator's assessment). Those who assess players' potential include scouts, coaches, and the media (Perry, 2017). Each evaluator, in turn, can observe players' strengths, speed, decision-making, technique, and attitude across many contexts (e.g. against various opponents, assisted by different teammates, and under diverse weather conditions) (Baseball America, 2017).

Next, per cohort, we regressed opportunity (i.e. a measure of resources) on overall pick number (i.e. a measure of potential):

$$Opp_{\mathrm{i}} = \beta_0 + \beta_1 Opk_{\mathrm{i}} + \beta_2 Opk^2_{\mathrm{i}} + e_{\mathrm{i}}, \tag{2}$$

such that subscript i refers to a player, β_0 is the intercept, β_1 and β_2 are regression coefficients, *Opk* is a player's overall pick number, Opk^2 is the squared value of *Opk*, and *e* refers to residual opportunities. We included Opk^2 in Equation 2 because top picks (i.e. closer to pick #1) may receive disproportionately larger amounts of opportunities. *Opp* refers to opportunities received during years 1 and 2 in MLB (i.e. number of plate appearances for batters, and number of innings pitched for pitchers). We aggregated opportunities in years 1 and 2 because the amount of opportunities a player receives may differ across years due to reasons other than potential (e.g. injury, team strategy requiring greater/less use of certain players). Equation 2 incorporates a time lag between its two predictors (*Opk* and Opk^2) and the criterion (*Opp*), in that the overall pick number is decided before one's debut to MLB (i.e. before accumulating value on *Opp*). To clarify, variability in overall pick numbers across players would not be the same across cohorts. This is because a cohort consists of players who played their first game in MLB in the same season but were not necessarily drafted in the same season. For example, Chip Ambres was drafted as the 27th pick in the 1998 new player draft, whereas Brian Anderson was drafted as the 15th pick in the 2003 new player draft. Yet, both players played their first MLB game in 2005.

By regressing opportunity on overall pick number-related variables per cohort, we operationalized potential-based allocation as an R^2 value per cohort, where each R^2 captures the extent to which resources (measured as opportunities) are allocated to workers in a cohort based on their potential (measured as overall pick number). In other words, each R^2 constitutes a data point for potential-based allocation at the cohort level of analysis. Our use of individual-level regressions to derive a higher (i.e. cohort) level predictor is equivalent to procedures used in past research, where individual-level regressions were used to measure the extent to which pay is allocated based on differences among workers in a unit (e.g. Trevor et al., 2012).

We also derived alternative operationalizations of potential-based allocation per cohort by aggregating opportunities over more distant years (i.e. beyond years 1 and 2): Opportunities allocated in years 2 and 3; years 3 and 4; years 4 and 5; and years 5 and 6. This was needed to assess our four competing hypotheses concerned with how the proportion of stars is predicted by potential-based allocation in early and later years.

Performance-based allocation

To measure performance-based allocation, we conducted two intermediate steps at the individual level by (1) specifying resources as opportunities to perform and (2) specifying performance as results produced on the focal job or position rather than what is predicted to happen before the job or position is occupied. In our context (i.e. MLB), we specifically operationalized performance in the following manner: For the performance of batters, we used on-base percentage (OBP), slugging percentage (SLG), and wins-above-replacement per plate appearance (WAR/PA). We chose these performance metrics for batters because the core job of a batter is to get on base (Lewis, 2003), and the three performance metrics capture this core job duty but in slightly different ways (e.g. OBP captures getting on base by getting hit by a pitch, whereas SLG more clearly captures the extent to which one gets one base through 'power' moves such as homeruns). For the performance of pitchers, we used earned run average (ERA), fielding independent pitching (FIP), and wins-above-replacement per inning pitched (WAR/IP). We chose these performance metrics for pitchers because the core job of a pitcher is to minimize the number of runs (i.e. going through all the bases and home plate) made by the opposing team, and the three performance metrics capture this core job duty but in slightly different ways (e.g. WAR/IP, in contrast to the other metrics, adjusts for pitcher positions such as starter versus reliever).

Next, we regressed opportunity (i.e. a measure of resources) on the aforementioned performance variables for each cohort:

$$Opp_i = \beta_0 + \beta_1 Perf_i + \beta_2 Perf^2_i + e_i, \quad (3)$$

such that subscript i refers to a player; β_0 is the intercept; $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are sets of regression coefficients; $\boldsymbol{Perf}$ is a vector containing the performance variables (i.e. WAR/PA, OBP, and SLG for batters, or WAR/IP, ERA, and FIP for pitchers)—calculated based on one's first year in MLB; $\boldsymbol{Perf}^2$ is a vector containing the squared terms of the performance variables; and e refers to residual opportunities. We included $\boldsymbol{Perf}^2$ in Equation 3 because the most highly performing individuals may receive disproportionately larger amounts of opportunities. Opp refers to opportunities received during one's second year in MLB (i.e. number of plate appearances for batters, and number of innings pitched for pitchers). Given that $\boldsymbol{Perf}$ and $\boldsymbol{Perf}^2$ are based on the first season while Opp is based on the second season, there is a one-year time lag between the two predictors ($\boldsymbol{Perf}$ and $\boldsymbol{Perf}^2$) and the criterion (Opp).

By regressing opportunity on performance variables per cohort, we derived an R^2 per cohort, where each R^2 captures the extent to which resources (measured as opportunities) are allocated to workers in a cohort based on their performance on the job. In other words, each R^2 constitutes a data point for performance-based allocation at the cohort level of analysis.

We also derived alternative operationalizations of performance-based allocation per cohort (i.e. beyond performance in year 1 and opportunities in year 2): Performance in year 2 and opportunities in year 3; performance in year 3 and opportunities in year 4; performance in year 4 and opportunities in year 5; and performance in year 5 and opportunities in year 6. This was needed to assess our four competing hypotheses, as they describe how the proportion of stars is predicted by performance-based allocation in early and later years.

Cohort-level control variables

We used six cohort-level control variables that may confound the relationship between potential- versus performance-based allocation and the proportion of stars: (1) opportunity-for-other-reasons, (2) cohort size, (3) games started, (4) games, (5) playoffs, and (6) final rank.

First, we included opportunity-for-other-reasons (i.e. the extent to which opportunities are allocated to players in a cohort based on their age at debut and their teams' winning percentage). More experienced players and those in more highly-performing teams may obtain more opportunities that are useful for becoming a star player. In addition, by controlling for teams' winning percentage per player per cohort, we account for the possibility that some cohorts may, on average, have had better coaches with greater training abilities compared to other cohorts. We measured opportunity-for-other-reasons by regressing opportunity on the player's age at debut and his team's winning percentage at the individual level of analysis:

$$Opp_i = \beta_0 + \beta_1 Age_i + \beta_2 WinPer_i + e_i, \tag{4}$$

where subscript i is a player, β_0 is the intercept, β_1 and β_2 are regression coefficients, and e refers to residual opportunities. *Age* is a player's age at debut in MLB. *WinPer*, or winning percentage, is the number of wins divided by the total number of games played by the player's team. *Opp* means opportunities received. We then applied Equation 4 per cohort to derive an R^2 for every cohort, where each R^2 substantively represents the extent to which opportunities are allocated to players in a cohort based on factors other than the players' potential or performance.

Cohort size refers to the number of players available when calculating each cohort's potential- or performance-based allocation. It is important to control for this variable because it is possible that the greater the cohort size (that is, the greater the number of players in a cohort), the better the capability to recruit players, including top players. For example, for calculating potential-based allocation, there were 80 batters in the 2006 batter cohort (consisting of batters who played their first MLB game in 2006), whereas the 2008 batter cohort contained 105 batters. Due to its larger number of batters, the 2008 batter cohort may have a greater advantage in producing a larger proportion of stars.

Games started refer to the number of games started per cohort. This control variable represents the degree to which starters are present and utilized in a cohort. Compared to relief pitchers and other types of specialists, starters assume a more generalist role and are likely to receive more opportunities. More opportunities allow players to generate more individual output, contributing to more team wins. As a result, the higher a cohort's value for games started, the greater may be the proportion of future stars produced in the cohort.

Games refer to the number of games played per cohort. For example, some cohorts can have fewer games played than others due to unusual events such as lockouts or strikes that would reduce the number of games played in a season. Cohorts with higher numbers of games may have greater proportions of future stars because more games mean more opportunities available per player, and players need opportunities to generate output and contribute to team wins.

Playoffs is another control variable representing the extent to which players' teams in a cohort advanced from the regular season to the playoffs (i.e. postseason). Given that '1' = made it to the playoffs versus '0' = did not make it to the playoffs per player in a cohort, we added all '1' values per cohort. We included playoffs to control for the fact that some cohorts have more players who advanced to the playoffs after a regular season. The higher the number of players who advanced to the playoffs in a cohort, it is likely that the cohort contains more players who enjoyed opportunities of higher quality (e.g. in games where teams were not eliminated from the playoffs)—opportunities that may be more beneficial for producing a greater proportion of stars. Conversely, the lower the number of players making it to the playoffs, the cohort likely contains fewer players who enjoyed higher-quality opportunities during the regular season.

Final rank is a control variable indicating the degree to which players' teams in a cohort ended their regular seasons successfully (i.e. at a higher rank in their division). Since a higher rank (i.e. closer to rank #1) for each player in a cohort means that the player's team ended its regular season more successfully than other teams, we calculated the average rank per cohort. We included final rank as a control variable because cohorts that are overall more highly ranked for a regular season also likely have more players who enjoyed opportunities of higher quality (e.g. in games where teams were not eliminated from the playoffs)—opportunities that could be more beneficial for producing a greater proportion of stars.

Results

Next, we describe our results on the four competing hypotheses concerned with whether and how potential- and performance-based allocation predict the proportions of stars in cohorts. Not all results discussed below refer to tables, given the need to conserve space. However, all tables of results can be found on the Open Science Framework site: https://osf.io/xxxx.

Q3

Test of H1

Main results

Tables 1 and 2 show results pertaining to potential-based allocation, where opportunities are aggregated across years 1 and 2. Table 1 shows descriptive statistics and correlations among the cohort-level variables.

Table 1. Descriptive Statistics and Intercorrelations Involving Potential-based Allocation (Opportunities Received in Years 1 and 2).

Variable	Mean	Standard deviation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Opportunity-for-other-reasons	.06	.05							
(2) Cohort size	63.24	20.85	.06 (.589)						
(3) Games started	628.3	276.5	−0.05 (.610)	.11 (.293)					
(4) Games	5,068	2,599	−0.06 (.554)	.66 (.000)	−0.39 (.000)				
(5) Playoffs	26.95	13.83	−0.03 (.794)	.75 (.000)	.24 (.025)	.60 (.000)			
(6) Final rank	3.81	.57	−0.15 (.160)	−0.66 (.000)	−0.18 (.095)	−0.24 (.022)	−0.61 (.000)		
(7) Potential-based allocation	.07	.11	−0.11 (.321)	−0.39 (.000)	.02 (.881)	−0.07 (.515)	−0.12 (.246)	.53 (.000)	
(8) Proportion of stars per cohort (α)	2.68	1.32	−0.01 (.892)	−0.08 (.464)	.08 (.460)	−0.06 (.564)	−0.05 (.614)	.01 (.922)	−0.17 (.113)

Notes. Number of cohorts (i.e. sample size) = $k = 90$. Each bivariate correlation coefficient is followed by its p-value in parentheses (two-tailed). Opportunity-for-other-reasons = extent to which opportunities are allocated to players in a cohort based on their age at debut and their teams' winning percentage, where opportunities refer to those received during one's first and second years in MLB; Cohort size = number of players available when calculating each cohort's potential-based allocation; Games started = number of games started per cohort during players' first and second years in MLB; Games = number of games played per cohort during players' first and second years in MLB; Playoffs = extent to which players' teams in a cohort advanced from the regular season to the playoffs (i.e. postseason); Final rank = degree to which players' teams in a cohort ended their regular seasons successfully (i.e. at a higher rank in one's division); Potential-based allocation = extent to which resources (operationalized as opportunities) are allocated based on workers' potential (i.e. predicted performance in a future job or position that the workers have not yet started), where opportunities refer to those received during one's first and second years in MLB; Proportion of stars per cohort (α) = power law's parameter (the smaller and closer the value of power law's α to 1.0, the heavier is the distribution's right tail, indicating a larger proportion of stars in the focal cohort).

Table 2 contains the results for two cohort-level regression models: Regression model A with only control variables, and regression model B with control variables and potential-based allocation. Regression model B in Table 2 shows that potential-based allocation's standardized regression coefficient is negative and statistically significant at $p<0.05$: β = −0.32 ($SE=0.14$, $p=0.022$, $k=90$), where *SE* is the standard error, *p*-values are two-tailed, and *k* is the number of cohorts. This means that potential-based allocation, operationalized as opportunities in years 1 and 2, predicts a greater proportion of stars—as smaller values of α closer to 1.0 are distributions with heavier right tails.

Though potential-based allocation is statistically significant when operationalized as opportunities in years 1 and 2, it is not in the following additional regression models of potential-based allocation using more distant time frames: Opportunities in years 2 and 3 (β = −0.15, $SE=0.13$, $p=0.270$, $k=90$); years 3 and 4 (β = −0.04, $SE=0.13$, $p=0.751$, $k=90$); years 4 and 5 (β = 0.00, $SE=0.13$, $p=0.986$, $k=90$); and years 5 and 6 (β = 0.13, $SE=0.13$, $p=0.345$, $k=90$). Overall, results do not support H1: Potential-based allocation, used in early and later years on the job, predicts a greater proportion of stars in cohorts.

Table 2. OLS Regression Including Potential-based Allocation (Opportunities Received in Years 1 and 2) to Predict the Proportion of Stars per Cohort (α).

	Regression model A: Control variables ($k=90$)	Regression model B: Control variables and potential-based allocation ($k=90$)
	β (*SE*, *p*)	β (*SE*, *p*)
Opportunity-for-other-reasons	−0.00 (.11, .989)	.01 (.11, .927)
Cohort size	−0.24 (.23, .299)	−0.40 (.23, .089)
Games started	.21 (.17, .221)	.25 (.16, .132)
Games	.23 (.24, .338)	.29 (.24, .223)
Playoffs	−0.16 (.21, .457)	−0.01 (.22, .947)
Final rank	−0.15 (.17, .390)	.03 (.19, .887)
Potential-based allocation		−0.32 (.14, .022)
	R^2 (*F*, *p*) = 2.74% (.39, .884)	R^2 (*F*, *p*) = 8.80% (1.13, .352)
		ΔR^2 (*F*, *p*) = 6.06% (5.45, .022)

Notes. *k* = Number of cohorts (i.e. sample size). Each standardized regression coefficient (β) is followed by its standard error (*SE*) and *p*-value (two-tailed); R^2 (*F*, *p*) = the model's multiple *R*-squared value and its *F*-statistic and *p*-value; ΔR^2 (*F*, *p*) = difference in the multiple *R*-squared value and its *F*-statistic and *p*-value when comparing Models A and B. Opportunity-for-other-reasons = extent to which opportunities are allocated to players in a cohort based on their age at debut and their teams' winning percentage, where opportunities refer to those received during one's first and second years in MLB; Cohort size = number of players available when calculating each cohort's potential-based allocation; Games started = number of games started per cohort during players' first and second years in MLB; Games = number of games played per cohort during players' first and second years in MLB; Playoffs = extent to which players' teams in a cohort advanced from the regular season to the playoffs (i.e. postseason); Final rank = degree to which players' teams in a cohort ended their regular seasons successfully (i.e. at a higher rank in one's division); Potential-based allocation = extent to which resources (operationalized as opportunities) are allocated based on workers' potential (i.e. predicted performance in a future job or position that the workers have not yet started), where opportunities refer to those received during one's first and second years in MLB; Proportion of stars per cohort (α) = power law's parameter (the smaller and closer the value of power law's α to 1.0, the heavier is the distribution's right tail, indicating a larger proportion of stars in the focal cohort).

Robustness checks

A specific rationale for H1 was that potential- and performance-based allocation may become positively correlated over time (though still distinct). To examine this possibility, and as a robustness check, we calculated five correlations between potential- and performance-based allocation within these five time-frames: (1) years 1 and 2; (2) years 2 and 3; (3) years 3 and 4; (4) years 4 and 5; and (5) years 5 and 6. For example, for years 1 and 2, we assessed the correlation between potential-based allocation (where opportunities are allocated in years 1 and 2 in MLB) and performance-based allocation (using performance in year 1 and opportunities in year 2). The five cohort-level correlations, respectively, are (1)0.04 ($p = 0.687$); (2)0.21 ($p = 0.043$); (3)0.07 ($p = 0.487$); (4) −0.11 ($p = 0.322$); and (5) −0.27 ($p = 0.009$), where $k = 90$ for all five correlations. As shown, potential- and performance-based allocation did not become more positively correlated over time.

We also examined the distinction between potential (determined before starting the job) and performance (on the job) at the individual level—which serves as the basis for the potential- versus performance-based allocation distinction at the cohort level of analysis. We calculated correlations between performance measures (e.g. on-base percentage for batters, earned run average for pitchers) and potential (i.e. overall pick number). The 36 correlations ranged from only −0.05 to 0.07 and did not show a pattern of becoming more positively correlated over time. Instead, potential and performance at the individual level of analysis remained largely distinct over time, suggesting that potential- and performance-based allocation at the cohort level also tend to stay distinct over time. H1 was again not supported.

Test of H2

Main results

In addition to results on potential-based allocation, we report results pertaining to performance-based allocation (performance in year 1 and opportunities in year 2), as shown in Tables 3 and 4. Regression model B in Table 4 shows that performance-based allocation's standardized regression coefficient is not statistically significant at $p < 0.05$: $\beta = -0.09$ ($SE = 0.08$, $p = 0.230$, $k = 268$).

The following shows results from additional regression models of performance-based allocation using more distant time frames: Performance in year 2 and opportunities in year 3 ($\beta = -0.05$, $SE = 0.09$, $p = 0.595$, $k = 269$); performance in year 3 and opportunities in year 4 ($\beta = -0.16$, $SE = 0.08$, $p = 0.048$, $k = 263$); performance in year 4 and opportunities in year 5 ($\beta = -0.26$, $SE = 0.08$, $p = 0.002$, $k = 253$); and performance in year 5 and opportunities in year 6 ($\beta = -0.21$, $SE = 0.09$, $p = 0.016$, $k = 248$).

Table 3. Descriptive Statistics and Intercorrelations Involving Performance-based Allocation (Performance in Year 1, and Opportunities in Year 2).

Variable	Mean	Standard deviation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Opportunity-for-other-reasons	.09	.09							
(2) Cohort size	43.60	21.54	−0.32 (.000)						
(3) Games started	256.2	137.59	−0.04 (.466)	.20 (.001)					
(4) Games	1,921	1,436	−0.32 (.000)	.86 (.000)	−0.18 (.004)				
(5) Playoffs	5.17	5.06	−0.21 (.001)	.71 (.000)	.15 (.017)	.54 (.000)			
(6) Final rank	4.35	.49	.00 (.947)	.20 (.001)	−0.03 (.571)	.31 (.000)	.31 (.000)		
(7) Performance-based allocation	.29	.17	.28 (.000)	−0.55 (.000)	−0.17 (.007)	−0.36 (.000)	−0.41 (.000)	.10 (.108)	
(8) Proportion of stars per cohort (α)	2.46	1.38	.12 (.045)	.02 (.760)	.04 (.474)	.01 (.871)	.04 (.469)	.01 (.823)	−0.05 (.428)

Notes. Number of cohorts (i.e. sample size) = $k = 268$. Each bivariate correlation coefficient is followed by its p-value in parentheses (two-tailed). Opportunity-for-other-reasons = extent to which opportunities are allocated to players in a cohort based on their age at debut and their teams' winning percentage, where opportunities refer to those received during one's second year in MLB; Cohort size = number of players available when calculating each cohort's performance-based allocation; Games started = number of games started per cohort during players' second year in MLB; Games = number of games played per cohort during players' second year in MLB; Playoffs = extent to which players' teams in a cohort advanced from the regular season to the playoffs (i.e. postseason); Final rank = degree to which players' teams in a cohort ended their regular seasons successfully (i.e. at a higher rank in one's division); Performance-based allocation = extent to which resources (operationalized as opportunities) are allocated based on workers' actual performance on the job, where performance refers to that during one's first year in MLB and opportunities refer to those received during one's second year in MLB; Proportion of stars per cohort (α) = power law's parameter (the smaller and closer the value of power law's α to 1.0, the heavier is the distribution's right tail, indicating a larger proportion of stars in the focal cohort).

Table 4. OLS Regression Using Performance-based Allocation (Performance in Year 1, and Opportunities in Year 2) to Predict the Proportion of Stars per Cohort (α).

	Regression model A: Control variables ($k = 268$)	Regression model B: Control variables and performance-based allocation ($k = 268$)
	β (*SE*, *p*)	β (*SE*, *p*)
Opportunity-for-other-reasons	.15 (.07, .023)	.16 (.07, .015)
Cohort size	−0.14 (.20, .498)	−0.23 (.22, .291)
Games started	.09 (.09, .303)	.10 (.09, .246)
Games	.15 (.18, .396)	.20 (.18, .277)
Playoffs	.09 (.10, .362)	.08 (.10, .382)
Final rank	−0.03 (.07, .679)	−0.01 (.07, .836)
Performance-based allocation		−0.09 (.08, .230)
	R^2 (*F*, *p*) = 2.47% (1.10, .362)	R^2 (*F*, *p*) = 3.01% (1.15, .331)
		ΔR^2 (*F*, *p*) = 0.54% (1.45, .230)

Notes. k = Number of cohorts (i.e. sample size). Each standardized regression coefficient (β) is followed by its standard error (*SE*) and *p*-value (two-tailed); R^2 (*F*, *p*) = the model's multiple *R*-squared value and its *F*-statistic and *p*-value; ΔR^2 (*F*, *p*) = difference in the multiple *R*-squared value and its *F*-statistic and *p*-value when comparing Models A and B. Opportunity-for-other-reasons = extent to which opportunities are allocated to players in a cohort based on their age at debut and their teams' winning percentage, where opportunities refer to those received during one's second year in MLB; Cohort size = number of players available when calculating each cohort's performance-based allocation; Games started = number of games started per cohort during players' second year in MLB; Games = number of games played per cohort during players' second year in MLB; Playoffs = extent to which players' teams in a cohort advanced from the regular season to the playoffs (i.e. postseason); Final rank = degree to which players' teams in a cohort ended their regular seasons successfully (i.e. at a higher rank in one's division); Performance-based allocation = extent to which resources (operationalized as opportunities) are allocated based on workers' actual performance on the job, where performance refers to that during one's first year in MLB and opportunities refer to those received during one's second year in MLB; Proportion of stars per cohort (α) = power law's parameter (the smaller and closer the value of power law's α to 1.0, the heavier is the distribution's right tail, indicating a larger proportion of stars in the focal cohort).

Performance-based allocation is again not statistically significant when using performance in year 2 and opportunities in year 3. However, performance-based allocation is statistically significant when using the other three more distant time frames (i.e. years 3 and 4, years 4 and 5, and years 5 and 6).

Taken together, results indicate that potential-based allocation is only statistically significant in the years 1 and 2 time frame, and performance-based allocation is only statistically significant in years 3 to 6. Since potential- and performance-based allocation are never statistically significant in the same time frame, results do not support H2: Both potential- and performance-based allocation, used in early and later years on the job, predict a greater proportion of stars in cohorts.

Robustness checks

As a robustness check, we also ran a joint regression model that includes both potential- and performance-based allocation after including all control variables. As expected, when potential- and performance-based allocation are in the same regression model, potential-based allocation is significant at $p < 0.05$ ($\beta = -0.34$, $SE = 0.14$, $p = 0.015$, $k = 90$) while performance-based allocation is not ($\beta = -0.18$, $SE = 0.12$, $p = 0.130$, $k = 90$). Hence, these results also do not support H2.

Test of H3

Main results

As previously described, potential-based allocation is only statistically significant in the years 1 and 2 time frame, while performance-based allocation is significant only in later time frames (i.e. years 3 to 6). In other words, potential- and performance-based allocation predict a greater proportion of stars separately and in succession, supporting H3: Potential-based allocation used in early years on the job predicts a greater proportion of stars in cohorts, while performance-based allocation does so when used in later years.

Given empirical support for H3, we conducted additional analyses that are more in-depth to assess its theoretical rationale, which consisted of two parts as discussed earlier in the Theory and Hypotheses section: (a) Potential becomes obsolete or at least remains constant in its importance over time whereas (b) performance becomes more relevant (i.e. the superior basis for allocating resources), such that managers would be willing to allocate resources more closely based on performance in later years. For this rationale to receive empirical support, it is important to see evidence of managers using potential-based allocation less or by largely the same amount over time while making greater use of performance-based allocation. In other words, potential-based allocation values (in terms of R^2) should decrease or stay largely constant, while performance-based allocation values (R^2) will increase over time. Our follow-up analyses revealed that mean values of potential-based allocation over different and more distant time frames were 0.07, 0.07, 0.07, 0.07, and 0.08, respectively. In contrast, mean values of performance-based allocation using different and more distant time frames were 0.29, 0.37, 0.41, 0.47, and 0.50, respectively. The fact that potential-based allocation stays mostly the same while performance-based allocation is seen steadily increasing over time supports the rationale for H3, that managers become willing to allocate resources more closely based on performance in later years, as performance becomes more relevant (while the importance of potential stays the same even if it does not become obsolete over time).

Robustness checks

An alternative rationale for H3 is that the significance of performance-based allocation in only later years is driven by allocation of resources based on widening performance differences between players, rather than managers allocating resources more closely based on performance as performance becomes more relevant compared to potential. This alternative rationale was ruled out because results showed that standard deviations (SDs) of performance between players remained quite stable or decreased slightly over time. As described in the Method section, we operationalized performance as on-base percentage (OBP), slugging percentage (SLG), and wins-above-replacement per plate appearance (WAR/PA) for batters. For pitchers, performance was operationalized as earned run average (ERA), fielding independent pitching (FIP), and wins-above-replacement per inning pitched (WAR/IP). For each performance metric, we calculated the SD per year over the first five years (where year 1 consists of players in their first year in MLB, year 2 consists of players in their second year in MLB, etc.). Results were as follows: (1) OBP: 0.092, 0.085, 0.081, 0.081, and 0.083; (2) SLG: 0.144, 0.132, 0.127, 0.129, and 0.129; (3) WAR/PA: 0.009, 0.007, 0.007, 0.007, and 0.006; (4) ERA: 2.006, 1.793, 1.681, 1.529, and 1.575; (5) FIP: 1.345, 1.190, 1.127, 1.045, and 1.080; and finally (6) WAR/IP: 0.021, 0.019, 0.018, 0.017, and 0.018.

Test of H4

Main results

As shown earlier, performance-based allocation is *not* statistically significant when using performance in year 1 and opportunities in year 2, as well as when using performance in year 2 and opportunities in year 3. Performance-based allocation is, however, statistically significant when using the other three more distant time frames (i.e. years 3 and 4, years 4 and 5, and years 5 and 6). Since performance-based allocation is statistically significant only in later years, our results do not support H4.

Robustness checks

We then conducted robustness checks where performance in performance-based allocation is aggregated over two years at a time, because one year may not long enough to reflect players' true performance. Results from alternative regression models of performance-based allocation are as follows: performance in years 1 and 2 and opportunities in year 3 ($\beta = -0.01$, $SE = 0.09$, $p = 0.910$, $k = 269$); performance in years 2 and 3 and opportunities in year 4 ($\beta = -0.16$, $SE = 0.08$, $p = 0.036$, $k = 263$); performance in years 3 and 4 and opportunities in year 5 ($\beta = -0.16$, $SE = 0.08$, $p = 0.044$, $k = 253$); and performance in years 4 and 5 and opportunities in year 6 ($\beta = -0.21$, $SE = 0.08$, $p = 0.011$, $k = 248$). These results also do not support H4, given the significance of performance-based allocation in later years only.

Discussion

We studied whether, how, and why potential- and performance-based allocation predict the proportion of star performers in cohorts. Results supported H3: *Potential-based allocation used in early years on the job* *predicts a greater proportion of stars in cohorts, while performance-based allocation does so when used in later years*. The other three hypotheses lacked empirical support. Our results offer contributions to theory and implications for practice, as described below.

Theoretical contributions to the star performance literature

Our main contribution is to show that the two ways of allocating resources we examined—potential- and performance-based allocation—are not rival mechanisms. Instead, they are parts of a more comprehensive framework predicting the proportion of stars in cohorts. One of the two resource allocation mechanisms, potential-based allocation, builds on the notion that early-career differences across workers have long-lasting effects. Theories related to potential-based allocation include cumulative advantage (Bothner et al., 2011; Merton, 1968), deterministic chaos (Boisot & McKelvey, 2011), and studies generally concerned with the effects of initial conditions (Aguinis et al., 2016; Andriani & McKelvey, 2009; Dahlqvist et al., 2000; Vancouver et al., 2016). This research stream suggests that allocating resources based on workers' early-career differences (e.g. their potential) will result in more and more resources going to higher-potential workers, who then snowball into a proportion of stars *via* positive feedback loops. The other resource allocation mechanism we examined, performance-based allocation, relies on theories stating that any positive feedback loops are temporary at best (Joo et al., 2017; McNatt & Judge, 2004; Salganik et al., 2006; van de Rijt et al., 2014). Earlier differences across workers thus have no, trivial, or only a temporary influence on more distal outcomes. If so, greater proportions of stars are created by allocating resources based on workers' actual performance on the job rather than potential for the job (assessed before they start the job). Our results suggest that potential- and performance-based allocation can be reconciled and integrated into a comprehensive framework, where potential-based allocation in early years and performance-based allocation in later years predict the proportion of stars in cohorts. This integrated view differs from past research and practitioner discussions framing potential- and performance-based allocation as rival mechanisms (e.g. Gallardo-Gallardo et al., 2013).

As another contribution, we offer an explanation for *why* potential-based allocation used in early years on the job predicts the proportion of stars in cohorts, while performance-based allocation does so when used in later years on the job: Performance becomes more important as the basis for allocating resources over time compared to potential, such that managers become willing to allocate resources more closely based on performance in later years. This proposed explanation is theoretically meaningful in that it can account for why some studies in the star performance literature supported using potential-based allocation (e.g. Aguinis et al., 2016; Andriani & McKelvey, 2009; Boisot & McKelvey, 2011; Bothner et al., 2011; Merton, 1968; Vancouver et al., 2016) while others supported using performance-based allocation (e.g. Joo et al., 2017; McNatt & Judge, 2004; Salganik et al., 2006; van de Rijt et al., 2014). Specifically, studies finding greater support for using potential-based allocation may have focused on early periods in workers' performance, which our study suggests is when performance is less relevant such that managers are less willing to allocate resources closely based on performance. In contrast, studies finding greater support for using performance-based allocation may have more heavily incorporated later periods in workers' performance, which our study suggests is when performance becomes more relevant such that managers are more willing to allocate resources closely based on performance.

Theoretical contributions to the RBT

Another contribution is to expand the RBT's role in explaining phenomena in the star performance literature. Research in the star performance literature has thus far used RBT logic to explain the value or consequences of having star performers (e.g. Aguinis & O'Boyle, 2014; Terry et al., 2023). Departing from such focus on explaining the consequences of stars, our study demonstrated how the RBT logic can be used to explain antecedent mechanisms leading to more stars. As described in our theory and hypotheses section, we used the RBT to theorize that allocating resources (e.g. opportunities) to individuals based on their potential or performance is equivalent to bundling VRIN resources, which then leads to a greater proportion of stars who are often sources of competitive advantages. Using the RBT, we further theorized *when* resource allocation based on potential versus performance constitutes the better bundle of VRIN resources might depend on the instability of the environment (i.e. the extent to which the environment is subject to dramatic or constant changes). Thus, our study contributes to expanding the RBT's domain by showing how the theory can help explain not only consequences but also antecedents regarding star performers.

Practical significance

Results suggest that increasing the proportion of stars is a matter of allocating more resources to workers with high potential in early years (i.e. years 1–2) and subsequently to workers with high performance in later years (i.e. years 3–6). In this section, we offer a practitioner-centric interpretation of our results, given the importance of communicating a study's meaning from the perspective of practitioners rather than simply stating results are statistically significant (Aguinis, 2025). Specifically, the relationship between potential-based allocation and the proportion of star performers in years 1–2 had a standardized regression coefficient of −0.32 (see Table 2). This negative regression coefficient denotes a *positive* association between the two variables because potential-based allocation was operationalized as an R^2 value, and the proportion of stars was operationalized using power law α for which smaller values closer to 1.0 indicate greater proportions of stars (i.e. distributions with heavier right tails). Thus, the −0.32 regression coefficient means that an increase in the use of potential-based allocation by one standard deviation (SD), which is 0.11 per Table 1, translates to an increase in the proportion of stars *via* a 0.32 SD decrease in power law α—that is, a 0.42 decrease in power law α given that the SD of power law α was 1.32 per Table 1, and 1.32 * 0.32 = 0.42.

Lowering the power law α by 0.42 is practically significant because it translates to a meaningful increase in the proportion of stars. For example, if the performance of employees is characterized by a power law α of 2.68 (which is the mean value of power law α shown in Table 1), a 0.42 decrease in power law α would result in a power law α of 2.26. Given such, we used the rPareto() function in R to simulate two power law distributions of employee performance with α values of 2.68 and 2.26 ($N = 1000$ for each distribution). In each power law distribution, the lowest value that could be simulated was 1, no upper limit was imposed, and thus each simulated value per distribution represents an employee's score on an objective performance dimension (e.g. sales) that is not artificially constrained by a performance ceiling (e.g. a 5 out of 5 on a Likert scale). Assuming that simulated values above 10 are considered star performers per distribution, the power law distribution with α of 2.68 contained two star performers exceeding the 10 threshold (i.e. 21.96 and 10.65). In contrast, in the power law distribution with α of 2.26, five star performers exceeded the threshold (i.e. 119.25, 31.79, 20.09, 14.81, and 13.62). Not only does the latter distribution (α = 2.26) enjoy a greater number of stars (more than double), but also the quality of the star performers differs considerably. For instance, the top-performing worker in the α = 2.26 distribution is 5.43 times more highly-performing than the top-performing worker in the α = 2.68 distribution (because 119.25/21.96 = 5.43). In highly competitive industries or workplace settings (e.g. high-tech, sales, sports), having more star performers of higher quality can help make a significant impact on key outcomes (e.g. successful innovation, making one's top competitor exit the market, winning the game).

As another illustration, the relationship between performance-based allocation and the proportion of star performers in years 4–5 had a standardized regression coefficient of −0.26, as described in the Results section. The −0.26 regression coefficient means that an increase in the use of performance-based allocation by one SD (i.e. 0.18) translates to an increase in the proportion of stars *via* a 0.26 SD decrease in power law α—that is, a 0.37 decrease in power law α given that the SD of power law α was 1.41 based on data used for this regression model, and 1.41 * 0.26 = .37. Lowering the power law α by 0.37 translates to a meaningful increase in the proportion of stars. For example, if the performance of employees is characterized by a power law α of 2.50 (which is the mean value of power law α based on data used for this regression model), a 0.37 decrease in power law α would result in a power law α of 2.13. We then simulated two power law distributions of employee performance with α values of 2.50 and 2.13 ($N = 1000$ for each distribution) using the rPareto() function in R. The power law distribution with α of 2.50 contained three stars exceeding the 10 threshold (i.e. 31.25, 17.99, and 11.59). In contrast, the power law distribution with α of 2.13 had four star performers exceeding the threshold (i.e. 116.84, 19.17, 15.72, and 11.91). Not only does the latter distribution ($\alpha = 2.13$) enjoy a slightly greater number of stars, but also the quality of the star performers differs considerably (i.e. each of the top three-performing workers in the $\alpha = 2.13$ distribution outperformed each of the top three in the $\alpha = 2.50$ distribution, respectively).

Generalizability and future research directions

Given our use of sports data, we clarify the extent to which our results and implications may generalize to non-sport industries or organizations. One likely factor is task interdependence (i.e. collaboration), which broadly consists of pooled and reciprocal interdependence. Pooled interdependence exists when workers contribute to a group goal mainly or only by completing separate individual tasks (Thompson, 1967). The sum of how well each individual completes one's task determines the group's performance in pooled interdependence contexts. For example, in baseball (which we used for our data), players do not need peer-generated opportunities (e.g. passes) from teammates to produce output (e.g. homeruns) (Foster & Washington, 2009; Harder, 1992; Keidell, 1987; Trevor et al., 2012). Instead, managers give opportunities required to produce output (e.g. plate appearances for batters). The sum of each output then largely determines a baseball team's performance. Due to the independent manner in which teammates contribute to team performance in baseball, it is quite feasible for stars to exert a positive effect on the team without undermining teammates' or the team's performance. This is consistent with past research showing that more stars are related to team performance in baseball (i.e. pooled interdependence) in a positive-linear manner—with possibly diminishing but not negative returns (Swaab et al., 2014). Thus, in industries or organizations characterized by pooled interdependence, increasing the proportion of stars may be better than having fewer stars, and our results and implications may help achieve that outcome.

In contrast to pooled interdependence, reciprocal interdependence exists when workers contribute to a group goal not only by completing separate individual tasks, but also by producing intermediate output that then becomes the input that other members in the group need to produce the final output (Thompson, 1967). For instance, a basketball player could use exceptional dribbling skills to advance all the way to the other team's basket and score points, but individual prowess alone is insufficient. More often, basketball players need an intricate set of intermediate outputs (e.g. passes) from teammates to produce final output (e.g. points scored) (Harder, 1992). Even Michael Jordan, known for his superb skills as an individual player, was immensely assisted by his teammate Scottie Pippen (Goode, 2011; Lowe, 2020) and vice versa (Apache, 2011). Such heavy reliance on teammates increases the team's vulnerability to damage by a non-collaborative star, who might hoard the ball to score more points, at the cost of intra-team coordination and team performance (e.g. lower chance of winning). To the extent that there is room for stars to hurt their group's performance in industries or organizations characterized by reciprocal interdependence, it may be better to reduce (not increase) the proportion of stars and invest more in team capabilities. Therefore, future research is needed to examine how our results, based on data characterized by pooled interdependence, generalize to settings characterized by reciprocal interdependence.

Another factor that likely limits the generalizability of our findings to non-sport settings is information abundance (or lack of it). The sports context is characterized by continuously observable individual performance, where behaviors usually generate results that are immediately viewed and even recorded. For example, after a baseball batter swings, the result is immediately seen (e.g. home run, foul ball). Also, scouts or sports managers tend to have access to abundant and often publicly available information about players (Lewis, 2003). Hence, although past research has discussed similarities between sports and other types of industries (e.g. Day et al., 2012), our results based on sports data may best apply to contexts where information about workers' performance is readily available and abundant (e.g. performance is constantly or regularly tracked, objective indicators of performance such as sales are available). However, our results may not be replicated (e.g. neither potential- nor performance-based allocation predict the proportion of stars), to the extent that potential or performance is not well measured in less data-rich settings (e.g. performance is not tracked regularly, performance metrics are less quantifiable). In such data-deficient settings, the more relevant task might be to make information about a firm or unit's employee performance more readily available and abundant to begin with. Firms or units that become more data-rich in terms of employee performance (e.g. by introducing systems or technologies to assist with measuring and storing performance information) may then be in a position to consider applying our empirical findings. This line of thinking suggests that information abundance may serve as a key moderator of the relationship between resource allocation mechanism (e.g. potential- or performance-based allocation) and the proportion of stars—an issue that may interest future research.

Limitations

One potential limitation is that our results may also not be relevant to very small cohorts. For example, managers in a very small organization with only two employees yet abundant resources could afford to invest in both employees as much as possible, rather than deciding which employee will receive more resources. Instead, our findings are more likely relevant to mid-size or large organizations or industry leaders who manage large cohorts of workers.

Moreover, our findings may not apply to contexts where star performers are mostly or entirely acquired rather than developed. To the extent that the proportion of stars is increased by acquiring them, managers need not try to predict who will become stars or how resources should be allocated to maximize the proportion of stars in the future. Instead, acquiring stars is a function of identifying already existing star performers. The results and implications from our study apply to contexts where stars are at least partly developed internally. To clarify, we focused on predicting and explaining the proportion of future stars produced from a pool of current non-stars, because internally produced stars have the potential to affect firm outcomes more heavily than externally acquired stars (Groysberg et al., 2004; Kor & Mahoney, 2000, 2004; Penrose, 1959)—though both approaches to increasing the proportion of stars are valuable and offer unique (dis)advantages (Kor & Leblebici, 2005).

Finally, our study is not a controlled laboratory experiment capable of more confidently ruling out alternative explanations (e.g. reverse causation) *via* different experimental conditions/manipulations. Nonetheless, given our non-experimental research design, we ensured sufficient time lags and incorporated various control variables. In particular, we incorporated a large time lag between the two predictors (i.e. potential- and performance-based allocation) versus the criterion (i.e. the proportion of star performers in cohorts), where the lag is about 21 years. This is because our criterion refers to cumulative output by year 27, whereas the two predictors encompass up to year 6, as described above. This large time lag makes it unlikely that our stated criterion affects our two stated predictors.

Conclusions

Potential-based allocation used in early years on the job predicted a greater proportion of stars in cohorts, while performance-based allocation did so when used in later years. This is likely because performance becomes more important as the basis for allocating resources over time, while the importance of potential stays the same even if it does not become obsolete. As a result, managers become willing to allocate resources more closely based on performance in later years. Our results contributed to theory by (1) integrating the two allocation mechanisms (i.e. potential- and performance-based allocation) into a more comprehensive framework predicting the proportion of star performers; (2) offering an explanation for why some prior studies in the literature supported using one mechanism rather than the other; and (3) expanding the RBT's role in the star performance literature to explain not only the consequences but also the antecedent mechanisms of star performers. From a practical significance perspective, we described how using potential- and performance-based allocation during different times based on our findings can translate to having more stars of higher quality (e.g. an organization having five star performers rather than two). Future research is needed to examine how our results based on MLB data may generalize to non-sport industries/organizations characterized by reciprocal interdependence or limited information on individual performance. We hope our study catalyzes future research aimed at predicting and explaining the proportion of stars.

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Disclosure statement

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No potential conflict of interest was reported by the author(s).

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Data availability statement

Data used for analyses in this study are available from the corresponding author.

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