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Performance under pressure and its impact on compensation: Evidence from professional basketball

Helmut M. Dietl [a], Steffen Q. Mueller [a,*], Marco Henriques Pereira [a], Markus Lang [b]

[a] University of Zurich, Plattenstrasse 14, Chair for Services & Operations Management, 8032 Zurich, Switzerland
[b] University of Lausanne, Quartier UNIL-Centre, Institute of Sport Sciences, 1015 Lausanne, Switzerland

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This paper investigates how performance in high- vs. low-pressure situations affects employee compensation. Leveraging sports as a natural laboratory, we analyze National Basketball Association (NBA) play-by-play data from 2004 to 2017 in combination with seasonal player salaries, using "clutch time"—the closing minutes during a game when the outcome is at stake and performance pressure is at its peak—as an objective criterion of performance pressure. Our regression analysis provides evidence of a salary premium for players who can excel under pressure. Whereas lower-paid players' performance does not differ much by pressure level, higher-paid players show exceptionally strong performance during critical phases of a game. We demonstrate that the ability to excel under pressure is greatly valued in professional basketball, raising the question of whether this ability is compensated not only in other sports but also in other sectors of the labor market.

1. Introduction

Performing well under pressure is an essential skill for success in various professional roles, such as paramedics, surgeons, firefighters, police officers, military personnel, and air traffic controllers. These jobs have in common that they require individuals to maintain focus, make quick decisions, and remain calm in high-stress situations, as the consequences of their actions can be significant, impacting lives, safety, and the success of their endeavors. However, performing well under pressure is crucial not only for jobs directly linked to the safety and health of others. Many professions demand positive performance despite pressure from time constraints or stressful situations, such as succeeding in examinations or job interviews, meeting deadlines, or interacting with employers, coworkers, and customers.

The importance of performance under pressure in evaluating and compensating employees is widely recognized (Cahlíková et al., 2020; Dohmen & Falk, 2011; González-Díaz et al., 2012; Nagler et al., 2023; Shurchkov, 2012). A large share of the previous literature investigates the phenomenon of "choking," the deterioration of performance in stressful situations despite possessing adequate skills and capabilities (Cohen-Zada et al., 2017; Essl & Jaussi, 2017; Baumeister, 1984), as well as the potentially underlying mechanisms (DeCaro et al., 2011; Eysenck et al., 2007; Mesagno & Beckmann, 2017; Sanders & Walia, 2012), and the role of individual factors such as personality traits (Bühren & Steinberg, 2019; Clarke et al., 2020; Uziel, 2007). In addition to choking, another strand of the literature focuses on the impact of performance-dependent pay on productivity (Ariely et al., 2009; Baktash et al., 2022; Franceschelli

* Corresponding author.
E-mail addresses: helmut.dietl@business.uzh.ch (H.M. Dietl), steffen.mueller@uzh.ch (S.Q. Mueller), marco.pereira@business.uzh.ch (M. Henriques Pereira), markus.lang@unil.ch (M. Lang).

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et al., 2010; Lazear, 2000). However, only few papers link performance under pressure with employee compensation (Deutscher et al., 2013; Hickman & Metz, 2015). In this paper, we contribute to the literature by providing the first systematic assessment of how performance in stressful work phases contributes to remuneration.

We empirically investigate the impact of high-pressure (HP) vs. low-pressure (LP) performance on employee compensation. To this end, we analyze a rich play-by-play dataset from the National Basketball Association (NBA), covering more than 7.5 million plays from the 2004/05 to 2016/17 seasons, that we combine with seasonal player salary data. Methodologically, we employ a fixed effects regression approach that links players' salaries to their overall performance in both HP and LP situations, using "clutch time"—the closing minutes during a game when the outcome is on the line and the pressure to perform at the highest level is at its peak—as an objective criterion of performance pressure. Moreover, we control for various player and contextual characteristics, ranging from standard determinants, such as age and experience, to attributes that could potentially be subject to labor market discrimination, such as the racial background of players.

Our findings show that employees who can increase their performance during critical work phases receive a salary premium. For players at the bottom of the salary distribution, we find relatively weak overall performance for both LP and HP situations, and they tend to perform worse in HP game phases than in LP game phases. Moving upwards the salary distribution, the better the players' performances in both low- and high-pressure situations and the higher the difference in their high- to low-pressure performances—players at the top of the salary distribution are able to increase their efforts to a maximum when a game outcome is on the line. To put it succinctly, being able to excel under pressure is clearly a strongly valued ability.

The main challenge to empirically investigating the relationship between employee productivity (in HP and LP scenarios) and compensation is the general lack of relevant data across most industries. Even in industries that pay employees according to their performance, available productivity metrics are commonly tied to overall job performance, skills, and accomplishments, none of which directly account for performance under pressure. Moreover, the impact of performing well under pressure is complex, not easily assessed or measured. In team-based work environments, for example, isolating the performance of an individual from the collective effort of the team is usually not possible. Likewise, defining objective criteria to measure high pressure, even within a given industry sector, is difficult because situations involving high pressure can vary greatly across working environments, depending on many external factors, such as task complexity, client base, and other market conditions.

Unlike traditional labor markets, professional sports markets allow us to easily measure and track employee performance, directly link individuals' performance to organizational outcomes, and take advantage of standardized working environments (Kahn, 2000). In particular, the NBA's uniform rules across all games allow for objective performance comparisons, with major external factors that could skew productivity being controlled (Berri & Krautmann, 2006). Additionally, data about worker compensation is readily accessible and transparent in this context. However, while a number of studies use sports markets to analyze the impact of productivity and specific employee characteristics on compensation (Fonti et al., 2023; Kahn, 2000), ours is the first study to investigate the potential impact of differences in overall performance during periods of high and low pressure.

Our findings not only provide insight into the implications of performance-dependent pay in LP and HP situations that are relevant for various industries, but also offer theoretical implications for the broader sphere of research in labor and personnel economics. Specifically, our work bridges and synthesizes two areas of research: performance under pressure and the determinants of salary premiums. Examples of such determinants include, in addition to performance (Baktash et al., 2022; Franceschelli et al., 2010), occupation type (Cortes, 2016), education (Lindley & Machin, 2016), and industry (Célérier & Vallée, 2019), age (Guvenen et al., 2021), and race (Chandra, 2000). In addition, our study directly links to behavioral economics research on sunk costs in managerial decisions (Keefer, 2021; Staw & Hoang, 1995) and the impact of peer expectations and social dynamics on performance and career success (Cialdini & Goldstein, 2004; Falk & Ichino, 2006; Merton, 1968). Furthermore, by investigating the impact of performance differences during periods of high and low pressure on compensation, we contribute to the literature on performance (in)consistency and pay (Lazear, 1998).

2. Literature review

Pressure can be defined as a subjective experience caused by "any factor or combination of factors that amplify the importance of delivering superior performance" (Baumeister, 1984, p. 610). Individuals experience *performance pressure* when they believe that they must perform well because their efforts will be closely scrutinized, leading to major consequences, such as positive rewards or unfavorable treatment (Gardner, 2012; Mitchell et al., 2019). High expectations and such potentially major consequences can motivate employees to excel under pressure (Baumeister, 1984; Mitchell et al., 2019). Yet, when experiencing performance pressure, individuals often exhibit diminished rather than improved performance, a phenomenon described as "choking" (Baumeister, 1984).

The mechanisms underlying decreased performance in HP scenarios are typically argued to impair sensorimotor skills in tasks that rely on automatic, well-practiced routines, such as operating machinery or concerting a free-throw in basketball (Baumeister, 1984; Beilock & Carr, 2001; Mesagno & Beckmann, 2017). In general, performance declines in HP situations can originate from two opposing mechanisms: *distraction* from the task due to external pressure (Sanders & Walia, 2012) or excessive *focus* on task execution, disrupting automatic processes (Baumeister, 1984). However, various contributions in psychology provide theoretical explanations for pressure-induced performance changes. *Drive Theories* suggest that performance is tied to arousal levels, with high arousal amplifying dominant responses linked to better performance (Zajonc, 1965). *Failure Avoidance Theory* proposes that audience expectations can enhance motivation or trigger choking if fear of failure dominates (Wallace et al., 2005). *Attentional Theories* focus on the cognitive resources and processes involved in a task (Mueller et al., 2022). For instance, the *Self-Focus Theory* argues that pressure-induced anxiety increases self-consciousness, disrupting automatic skills because of distraction (Baumeister, 1984; Mesagno & Beckmann, 2017). *Explicit*

Monitoring Theory attributes choking to overthinking and excessive focus on task execution, impairing performance in standardized skill tasks (DeCaro et al., 2011). However, according to *Attentional Control Theory*, individuals who can adjust for the negative effects of anxiety do not perform worse under pressure (Eysenck et al., 2007). Yet, there is no consensus on the exact mechanisms behind performance changes under pressure (Beilock & Gray, 2007; Böheim et al., 2019; Hill et al., 2010; Mesagno & Beckmann, 2017).

Most empirical studies on performance under pressure investigate the phenomenon of choking. For instance, Smith (2013) uses National Spelling Bee data to examine how students' performances of cognitive tasks are affected by their peers' performances. The results suggest that, if the previous competitor spelled a word correctly, the likelihood of the subsequent student making an error is significantly greater than if the preceding competitor had misspelled the word. Likewise, many studies provide evidence of diminished performance under time pressure (Kocher et al., 2019; Shurchkov, 2012). In line with theoretical considerations (Baumeister, 1984; Sanders & Walia, 2012), conducting a laboratory experiment, Ariely et al. (2009) find that high stakes—a proxy for pressure (Hickman & Metz, 2015)—increase performance in effort-based tasks but impair performance in skill-based tasks. Supporting these considerations, Harb-Wu and Krumer (2019) find that biathletes competing in their home country perform better in skiing (effort-based) but worse in shooting (skill-based). Similarly, Baumeister & Steinhilber (1984) document a "home disadvantage" for complex skill-based tasks that they attribute to audience-induced monitoring pressure. Moreover, analyzing European football league, the findings of Dohmen (2008) suggest that home team players score penalties more frequently than players from the away team. In contrast to these results, Ferraresi and Gucciardi (2021) analyze the Covid-19 "ghost games" from top-tier football leagues and find that the probability of missing a penalty increases for home teams playing without the presence of attending spectators, but decreases for away teams. Further examples for evidence of choking in sports include tennis (Cohen-Zada et al., 2017; Paserman, 2023), golf (Hill et al., 2010), and skiing (Bühren et al., 2024).

While playing a subordinate role in overall performance, free throws in basketball provide the opportunity to investigate choking during a situation that involves a single player without any potential interaction with other players. Similar to football players' regular training of shooting penalties, professional basketball players extensively practice scoring free throws. Hence, it can be assumed that such tasks are rather skill-based, because changes in effort are not likely to substantially impact performance (Böheim et al., 2019). Previous research provides some evidence that professional basketball players' free-throw performance tends to decrease under pressure; however, in general, evidence is mixed (for a literature review, see Goldschmied et al., 2022). For instance, analyzing NBA data from 2002 to 2013, Toma (2017) finds that in the final 30 seconds of a very tight game (when the shooter's team point difference ranges from −2 to 1), scoring a free throw is 0.97 percentage points less likely. Similarly, Cao et al. (2011) examine NBA data from 2002 to 2010 and find that players shoot on average 5 to 10 percentage points worse in the final seconds of very close games; however, they find no evidence of decreased performance when games are tied in the final 15 seconds. Moreover, they do not find evidence of free-throw performance under pressure being affected by differences between home and away games or the number of attending fans. Conversely, using NBA data from 2007 to 2016 and leveraging weather-driven variations in game attendance, Böheim et al. (2019) identify a significant negative effect of larger audiences on players' free-throw performance for home teams in non-critical early-game periods. For players of the away team, they do not find attendance to impact their performance.

In addition to empirical evidence that pressure can negatively impact performance, there is also evidence that moderate (or optimal) pressure can instead improve performance, potentially leading to exceptional achievements (Janssen, 2001). For instance, Barnes et al. (1983) analyze the pressure ("stress") on academic performance that can be attributed to parents, supervisors, and peers. Their findings suggest that, while parental pressure impairs performance, pressure from supervisors and peers enhances academic performance. Jane (2022) analyzes Major League Baseball games and finds that non-star players choke under pressure, while star players excel. Analyzing World and European Football Cup penalty shoot-outs, Savage and Torgler (2012) show that the likelihood of scoring the decisive penalty decreases for the trailing team, but increases for the leading team. Moreover, in contrast to previous findings of choking during football penalties (Dohmen, 2008), a recent study by Bühren and Gabriel (2023) analyzes handball penalties and finds that players do not choke during HP situations; on the contrary, they perform best when it matters most.

While typically associated with choking and decreased performance under pressure, failure avoidance, drive and attentional theories also provide explanations for the underlying mechanisms of increased performance under pressure. Potentially major positive and negative consequences can motivate to excel under pressure as well (Baumeister, 1984; Gardner, 2012; Mitchell et al., 2019). However, in the context of high-performers and star employees, various other phenomena may play a role in the relationship between performance under pressure. For instance, Merton's (1968) Matthew Effect poses an explanation for star players to being better at handling pressure than regular players, as it highlights how systemic factors, rather than pure talent, can shape long-term success. In sports, the Matthew Effect refers to the phenomenon where early success or advantages lead to further opportunities, better training environments, and recognition, reinforcing the initial advantage. This creates a cumulative cycle of success for some athletes, potentially reducing their anxiety and fostering their confidence, while others may struggle to catch up despite similar potential. It is therefore reasonable to assume that, on average, athletes profiting from the Matthew Effect perform better under pressure than regular athletes. Similarly, sunk costs, such as a high salary for a player, can bias managers' decisions about which players should play and how much playing time they receive, even when it may not align with optimal team performance (Keefer, 2021; Keefer, 2017; Staw & Hoang, 1995). Hence, if players receive more playing time from such biased manager decisions, they can be assumed to spend more time in HP game scenarios and thus have more experience competing under pressure, making them less prone to choking.

Directly linked to performance changes in situations of low and high pressure, González-Díaz et al. (2012) introduce a concept of *general* and *critical ability*. General ability refers to the ability to perform well on average, critical ability pertains to adjusting one's performance according to the importance of the situation. To assess the impact of critical ability on performance, they use tennis within-game point-level data, which has the advantage that every point in the match can be assigned a different level of importance (González-Díaz et al., 2012; Paserman, 2023). Their analysis reveals substantial heterogeneity in players' critical ability that directly relates to their ratings and rankings, highlighting the importance of identifying crucial situations and excelling under pressure as determinants for career success.

Moreover, social dynamics can significantly influence individual productivity, particularly under pressure (Cialdini & Goldstein, 2004; Falk & Ichino, 2006). Although the Brazilian national football team is comprised of highly skilled and experienced individuals, they collectively choked during the Semi-Final of the World Cup 2014, allowing the German team to score four goals within six minutes. In the context of sports, peer and role-specific expectations may further amplify this phenomenon. Star players are typically expected to take charge and perform decisively in clutch moments, while role players are tasked with executing disciplined and specific responsibilities (Paine, 2015). This division of expectations may lead to contrasting psychological experiences. Stars could face higher pressure due to performance scrutiny, while role players may experience stress from their limited but critical contributions.

Further exploring the complex interplay between pressure and productivity, the performance-pay literature reveals a potential avenue for harnessing the positive impact of pressure in the workplace. By aligning employee and organizational goals, performance pay can transform pressure into a stimulant to improve job performance (Lazear, 2000). Specifically, performance-dependent pay is positively related to higher productivity and earnings because it encourages greater effort and, as a consequence, attracts employees who possess higher abilities (Booth & Frank, 1999). However, performance pay also creates an environment in which employees feel pressured to perform well, and various studies show that such work-related stress can deteriorate employee health (Baktash et al., 2022; Buckert et al., 2017; Feri et al., 2013). Hence, achieving a delicate balance between too little and too much pressure in the workplace is critical to sustaining high, long-term employee productivity.

However, which factors determine that some individuals excel under pressure whereas others' performance decreases? One factor appears to be the degree of individual risk preferences. Conducting a laboratory experiment involving effort tasks, Essl and Jaussi (2017) examine how loss aversion affects performance under (time) pressure. The results demonstrate that individuals with high loss aversion tend to choke under pressure—they take longer to respond and are less successful at avoiding penalties. Another factor appears to be gender. Cahlíková et al. (2020) conduct a laboratory experiment using tournaments and psychosocial pressure and find that women choke under pressure but men do not; however, evidence regarding systematic differences in performance under pressure by gender are mixed (Böheim et al., 2019; Booth & Nolen, 2022; Bühren & Gabriel, 2023; Cohen-Zada et al., 2017). Other relevant factors include personality traits: For example, surveying archers and golfers about non-display of imperfection, doubts about taking action, and fear of a bad evaluation, Clarke et al. (2020) are able to predict the majority of athletes who reported instances of choking. Using tennis field experiment data, Bühren and Steinberg (2019) find that players with low self-esteem experience a first-mover advantage, whereas players with high self-esteem perform better as a second-mover. Related, Otten (2009) finds athletes perform better when their performance is recorded on video. He explains this by pointing to the athletes' stated sense of control, which boosts confidence and, in turn, performance. Moreover, according to Uziel's (2007) *meta*-analysis of experimental research, pressure has a generally beneficial impact on performance when the agent is an extrovert with a high sense of self-worth.

In conclusion, performance declines under pressure are most common in skill-based tasks with high stakes during crucial moments that can decide over failure or success. However, the net effect of pressure on performance also depends on the specific task and context, social environment, and individual characteristics. However, while the performance-pay literature primarily focuses on productivity, the performance-under-pressure literature largely overlooks the connection between performance and compensation. To the best of our knowledge, only two studies establish a connection between performance under pressure and compensation (Deutscher et al., 2013; Hickman & Metz, 2015). Hickman and Metz (2015) use professional golf data to investigate the influence of pressure on performance. Their analysis of the golfers' performance on the final putt of a tournament reveals a negative correlation: as potential monetary rewards increase, performance declines.

Deutscher et al. (2013) investigate the relationship between "mental strength" and compensation in basketball. They measure mental strength by comparing players' ability to make free throws in HP vs. LP situations during four NBA seasons (2003/04 to 2006/07). Their results suggest that a higher ratio of successful free throws in HP vs. LP situations increases a player's salary. While offering important insights, Deutscher et al. (2013) focus primarily on free-throw performance, whereas our study expands the scope by analyzing a wide range of performance metrics, including shooting accuracy, assists, rebounds, and defensive actions. Covering 13 seasons, our study is based on a comprehensive dataset, offering a robust foundation for examining the full range of skills essential in high-pressure situations.

3. Data, empirical strategy, and descriptive analysis

3.1. Data cleaning and specification of pressure situations

The sample of our analysis covers 7,588,492 observations of NBA play-by-play data, covering 16,797 games from the 2004/05 to 2016/17 (regular and playoff) seasons. To assess the impact of worker performance under pressure on their remuneration, this paper distinguishes between HP and LP situations. Unlike traditional workplaces, professional sports markets provide data that allows us to make use of standardized labor environments and specify HP work phases in a consistent and objective manner. We define HP situations as plays occurring during "clutch time" and LP situations as plays that do not. The official definition of clutch time is "the final 5 minutes of the fourth quarter or the overtime when the score is within five points" (nba.com). Hence, two conditions must be met for a play to be classified as an HP situation. First, the game has to occur within the last 5 minutes of the fourth quarter or during overtime when the game is extended. Second, the score difference between the two competing teams must be within 5 points, i.e., no team is leading by more than 5 points.

We aggregate the play-by-play data to the player-season level to link individual workers' overall performance in HP and LP situations with their seasonal compensation, resulting in a 13-season panel dataset covering 5,062 observations from 1,100 distinct players. The 16,797 games used to construct this dataset include 8,806 games with HP situations. However, because not every player was involved in games with HP situations in each season, we discard 416 observations, resulting in a final panel dataset with 4,646 observations featuring 1,004 players. We collected the data from basketball-reference.com (player characteristics), espn.com (play-by-play data, player characteristics, and complementary salary data), figshare.com (players' race), and nba.com (main salary data and player characteristics).

3.2. Empirical model and variable specifications

For our analysis, consider the following empirical model:

$$Ln\left(Salary_{pts+1}\right) = \gamma LPP_{pts} + \theta(HPP - LPP)_{pts} + \varphi X_{ps} + TS_{ts} + \epsilon_{pts} \tag{1}$$

$Ln(Salary_{pts+1})$ is the dependent variable and represents the salary for player p of team t in season $s+1$. Given the ambiguous direction of causality between players' salaries and their performances in each season, we follow the standard approach in the literature and use player salaries of the subsequent season due to the forward-looking nature of player contracts; likewise, we employ the natural logarithm, ensuring the salary data aligns more closely with a normal distribution (Deutscher et al., 2017; Hall et al., 2002). Moreover, we use inflation-adjusted salaries (base year 2005) to address changes in the economic landscape and obtain a more adequate representation of player compensation.

LPP_{pts} [HPP_{pts}] is the mean of the LP [HP] overall performance of player p of team t in season s, and $(HPP - LPP)_{pts}$ is the difference between a player's HP and LP performance. X_{pts} is a vector of control variables (e.g., age, height, position, and race). TS_{ts} represents a team-season fixed effect (FE) and ϵ_{pts} is the error term. The model is estimated via least squares dummy variable regression. Moreover, considering the error term structure in regression analysis of player salaries, the disturbance terms are likely correlated within observations of the same players. As a result, we allow for arbitrary error term correlations between observations of the same players by computing heteroscedasticity robust (Huber/White) standard errors clustered at the player level.

To measure employees' overall productivity in HP and LP work phases, we combine various performance metrics derived from the play-by-play data by computing the "Win Score" (Berri et al., 2006). This measure has been widely recognized and used as a holistic performance measure in prior research (Beus et al., 2014; Schmidt, 2021; Sieweke et al., 2017). It covers offensive and defensive metrics and provides a balanced measure of a player's overall performance by combining their positive contributions (points, rebounds, assists) and deducting for actions that detract from their team's success (missed shots, turnovers, fouls). Specifically, the Win Score for player p of team t in season s is defined as follows:

$$\begin{aligned} WinScore_{pts} = {} & Points_{pts} + Rebounds_{pts} + Steals_{pts} + \frac{1}{2}Assists_{pts} + \frac{1}{2}BlockedShots_{pts} - FieldGoalAttempts_{pts} - Turnovers_{pts} \\ & - \frac{1}{2}FreeThrowAttempts_{pts} - \frac{1}{2}PersonalFouls_{pts} \end{aligned} \tag{2}$$

The use of fractional weights reflects the varying significance of certain actions in basketball. *Points* represents the points scored by a player is a direct measure of offensive success. A Rebound occurs when a player retrieves the ball after a missed field goal or free throw attempt, and *Rebounds* equals the number of rebounds (offensive and defensive) secured by a player. Rebounding is a critical part of the game, as it allows a team to either maintain possession (on offense) or gain possession (on defense). *Steals* is the number of times a player successfully takes the ball away from the opposing team, indicating defensive performance. An *Assist* reflects the player's ability to facilitate scoring opportunities for their team. It is credited to a player who passes the ball to a teammate in a way that directly leads to a made basket. A *Blocked Shot* occurs when a defensive player legally deflects or stops an opponent's shot. *Field Goal Attempts and Free Throw Attempts* are the number of unsuccessful field goals and free throws, respectively. These terms penalize inefficient shooting. Likewise, *Turnovers* are instances where the player loses possession of the ball, they decrease the team's offensive opportunities. A *Personal Foul* is a violation that occurs when a player makes illegal physical contact with an opponent, impeding their movement or ability to play. They can negatively impact the team, such as giving opponents free throws or removing the player from the game.

We first compute the individual performance metrics, which are comprised by the Win Score, for each player for both HP and LP situations at the game level; then, we scale them on a per-minute basis not only because of the frequency and duration of HP compared to LP situations, but also because individual players spend different amounts of time in each context. In the second step, we compute the mean of the HP and LP Win Scores at the player-season level. In this context, it is important to acknowledge that the Win Score is affected by interactions between a player, his teammates, and his opponent(s). As an example, a rebound positively contributes to the Win Score, yet it invariably stems from a missed shot by either a teammate or an opponent. Likewise, a steal can result from a strong performance by a defending player or a weak offensive performance by his opponent. Consequently, the apparent enhancement of a player's performance under pressure may also be attributable to a decline in his opponents' performance. However, by computing the Win Score over an entire season, the metric averages out anomalies or biases caused by specific game contexts, such as home vs. away biases—the influence of crowd pressure or court familiarity is distributed over many games—and variations in opponent quality and performance. Hence, the aggregation reduces the noise introduced by situational factors, making the Win Score a robust measure of sustained performance. Moreover, the interplay between players is inherent to basketball, and metrics like rebounds and steals reflect a player's ability to excel within these dynamics: While a rebound depends on a missed shot, the ability to secure it consistently over a season signals good positioning, anticipation, and effort. Whether a steal reflects a player's skill or an opponent's mistake, the player's ability to capitalize on such opportunities consistently showcases defensive competence. Hence, while individual statistics like rebounds or steals partly depend other players' performance, the Win Score, when aggregated over a season, reflects a player's sustained ability to leverage opportunities and minimize errors.

In addition to the main independent variables of interest (players' Win Scores in HP and LP situations), we incorporate several control variables to account for potential confounding factors. Similar to previous research, we include a player's age, height, race, position, preferred throwing hand, draft position, and whether he participated in the "NBA All-Star game" of the current season (e.g., Chandra, 2000; Lindqvist, 2012; Müller et al., 2017). To specify race, we use the player-to-race mapping provided by Wen (2018), who analyzes labor-market discrimination in the NBA using player data from the 1999/00 to 2015/16 season. Wen (2018) manually collected information and photos using online sources such as Wikipedia, Facebook, Google, and Basketball Reference. We extended the mapping to the 2016/17 season using the same strategy. In this context, we decided to not extend the data and mapping any further because of potential biases arising by regulatory changes in player compensation starting in the 2017/18 season (see nbpa.com for details, a summary of changes is provided by moorebasketball.com). Moreover, the computation of team-season fixed effects requires assigning each player one team per season. However, sometimes players switch teams during a season or are lent to other teams for some games. We are approaching this issue by assigning each player a primary team per season based on the maximum number of games played per team per season. Likewise, we build the sum of the salaries a player received from different teams when competing for multiple teams within a season.

Last, we have to consider the potential impact of salary restrictions in the NBA, as they may bias our regression estimates. Specifically, according to regulations in the NBA's collective bargaining agreement, player salaries are capped at the lower and upper levels and as so-called minimum and maximum contracts. However, the majority of NBA players earn salaries that are neither at the minimum nor the maximum levels. The capped segments of the distribution (minimum and maximum contracts) affect a smaller subset of players, minimizing their overall influence on regression estimates. In addition, even for players earning near the maximum or minimum, salary variation exists: Maximum contracts depend on experience and tenure, with different tiers (e.g., rookie maximum vs. veteran maximum) and minimum contracts vary based on years of service, ensuring that some degree of differentiation remains, even within capped groups. Moreover, caps primarily affect absolute salary levels but do not necessarily distort the relative ranking or relationships within the distribution. Over time, salary caps adjust to reflect changes in league revenue, ensuring that player compensation trends broadly align with market forces. This stability minimizes systematic distortions in regression analyses over multiple seasons. Most importantly, the NBA employs a "soft salary cap" and a "luxury tax" that allow teams to spend above the salary cap under specific conditions. In contrast, the National Football League (NFL) and the National Hockey League (NHL) employ a "hard salary cap". However, past studies show that average league payrolls are commonly above the caps and large-market owners violate the salary cap both frequently and by large margins (Quirk & Fort, 2018). Hence, although the NBA's soft cap imposes constraints on certain segments of the salary distribution, it does not fundamentally alter the relationship between player performance and compensation.

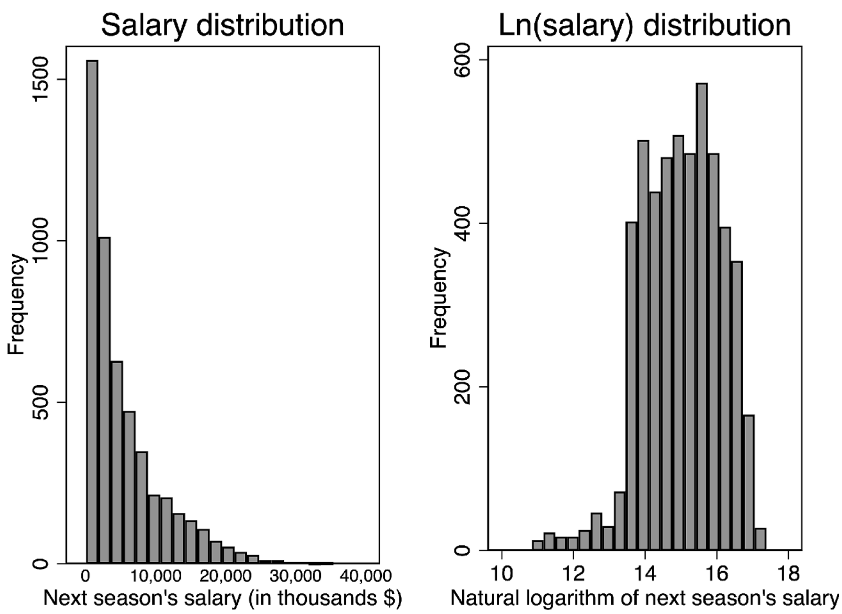

Fig. 1. Histograms of salary distribution. Note: Salary distributions based on 4,646 observations at the player-season level covering the seasons 2004/05 to 2016/17. Salary is deflated using 2005 as the base year.

3.3. Summary statistics and descriptive analysis

Fig. 1 shows histograms visualizing the distribution of players' deflated salaries for the next season (in levels and logarithmized); Table 1 provides summary statistics for the variables considered in our analysis.

As expected, the salary distribution skews to the left (Fig. 1, left panel), but following the natural logarithm transformation, it conforms more closely to a normal distribution (Fig. 1, right panel). Considering the summary statistics presented in Table 1, players earn an average salary of 5.8 million USD (inflation-adjusted) with significant dispersion as reflected by a standard deviation (SD) of 5.5 million USD. The average player age is 27.29 years, with the youngest being 19 and the oldest 42. Like differences in examination grades and in the quality of degrees associated with different universities, all-star status and draft position are indicators of the most promising workers and players, respectively. The NBA consists of 30 teams, and each team receives two picks for the annual player draft, resulting in a maximum [minimum] draft position of 60 [1]. The lowest player value corresponds to the highest draft position, and following a standard approach in the literature, we assign the draft position 61 to players who entered the league without being drafted.

Player-season combinations of NBA All-Stars constitute 7 % of our sample; the mean draft position is 25. The sample's average player height is 201.07 cm. Earl Boykings is the shortest player at 165 cm and the second smallest NBA player in history. The tallest player is Yao Ming at 229 cm. Of the players, 14 % play as centers, 43 % as forwards, and the remaining 43 % as guards. Regarding players' racial backgrounds, 69 % are Black, 9 % are of mixed race (i.e., Black-White), 21 % are White, and only 1 % are of other races (e.g., Asian). Most players (92 %) use their right hand for shooting, 8 % use their left, and only a few are ambidextrous.

Highlighting the elite caliber of NBA players and suggesting that they exhibit commendable aptitude for handling pressure, we find overall performance to be higher during HP than LP phases of a game. With a value of 0.42, the mean HP performance (Win Score) is approximately twice as high as the mean LP performance. In line with theoretical considerations, players appear to increase their effort to a maximum when a game outcome is on the line. Similarly, the dispersion and range of minimum and maximum performance under HP (SD = 2.96) are more extreme than under LP (SD = 0.13), which can be attributed partly to the transient nature of HP situations. However, instead of choking under pressure, on average, we find players tend to excel in the critical phases of a game when measured via a holistic performance measure.

To further analyze clutch performance and previous findings concerning choking under pressure and free-throw success, we compute mean values for individual performance metrics during HP and LP game phases (Appendix Table A.1) and, in addition, plot the HP-LP difference in the mean values for assists, blocks, steals, free-throw ratio, two-pointer ratio, and three-pointer ratio by season in Fig. 2.

First, players make 74.70 % of their attempted free throws during HP and 73.43 % during LP situations. On average, we find that players perform 1.27 percentage points better during clutch time, indicating they thrive under pressure rather than choke. Moreover, Fig. A.1 shows that the HP-LP free-throw ratio difference does not largely vary by season, ranging from approximately −1 to 3 percentage points; players only perform worse during HP situations in 3 out of the 13 seasons analyzed.

Second, with a difference of −0.86 [0.62] percentage points, players perform slightly worse [better] in making two pointers [three pointers] during clutch time. The HP-LP two-pointer ratio [three-pointer ratio] difference is relatively consistent over time [indicates a declining trend], ranging from approximately −2 to 1 [-2 to 3.5] percentage points. Moreover, with 0.251 HP vs. 0.23 LP [0.161 HP vs. 0.074 LP] attempts per minute, we find only slightly more [approximately twice as much] two-pointer [three-pointer] attempts during

Table 1
Variable summary statistics.

Variable	Mean	SD	Min	Max
Next season's salary	5,840,795	5,510,509	51,012	35,344,988
Ln (next season's salary)	15.115	1.043	10.840	17.381
Low pressure performance	0.219	0.125	−1.373	2.740
High pressure performance	0.416	2.963	−60.000	46.915
High minus low pressure Win Score	0.197	2.956	−60.195	46.784
Age (in years)	27.438	4.141	19.000	42.000
This season's All-star player	0.072		0	1
Draft position	25.252	19.311	1.000	61.000
Height (in cm)	200.879	9.035	165.100	228.600
Position: Center	0.137		0	1
Position: Forward	0.431		0	1
Position: Guard	0.432		0	1
Race: Black	0.687		0	1
Race: Black-White	0.094		0	1
Race: Other	0.007		0	1
Race: White	0.212		0	1
Shooting hand: Right	0.913		0	1
Shooting hand: Left	0.086		0	1
Shooting hand: Both	0.001		0	1

Note: Data include 4,646 observations at the player-season level derived from 7,588,492 observations of NBA play-by-play data covering the regular and playoff seasons 2004/05 to 2016/17. Salary is deflated using 2005 as the base year. Performance measured via the Win Score (see Section 3.2 for details).

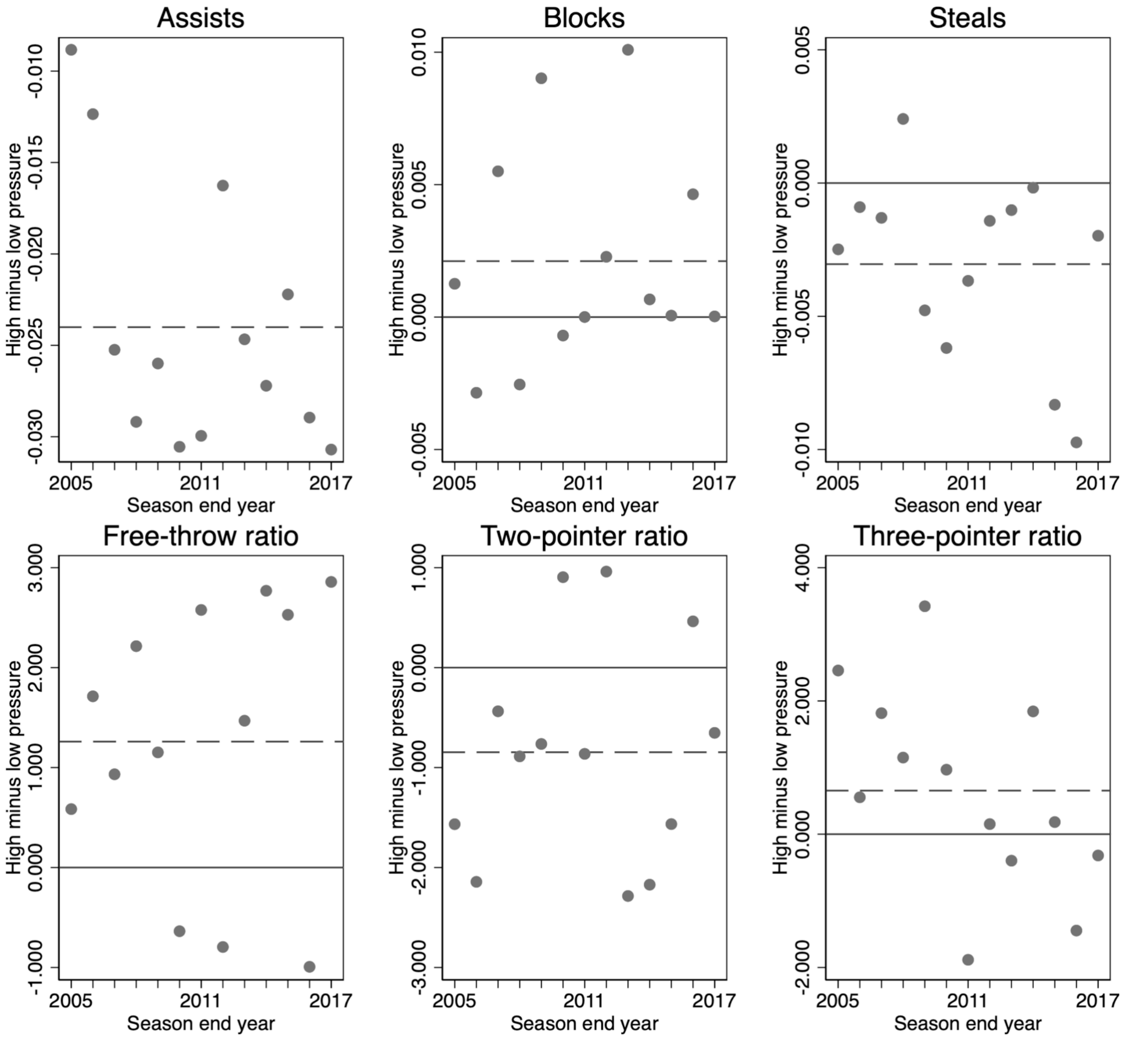

Fig. 2. Mean values of high- minus low-pressure performance statistics by season year. Note: Data include 4,646 observations at the player-season level derived from 7,588,492 observations of NBA play-by-play data covering the regular and playoff seasons 2004/05 to 2016/17. Individual performance metrics are scaled on a per-minute basis. Dashed lines indicate mean values.

HP game phases. As scoring three pointers is highly relevant to win tight games during the final minutes, the increased three-pointer performance is in line with our findings of increased free-throw performance during clutch time—players, on average, are able to increase their effort to a maximum when a game outcome is on the line. This finding is supported by players scoring approximately 60 % more points per minute during HP situations.

Moreover, we find approximately 33 % more assists during LP compared to HP phases of a game; the mean HP-LP difference is negative in all seasons under consideration. As a reasonable explanation, players may avoid passing the ball in HP phases because it takes more time to score and, in addition, they may try to make game-deciding points themselves, rather than assisting, to distinguish themselves during clutch time in an attempt to increase their popularity and market value. Concerning blocks and steals, the differences between HP and LP situations are relatively small but consistent across seasons. On average, we find approximately 8.7 % more blocks [11 % less steals] during clutch time. Furthermore, we find roughly twice as many turnovers and rebounds.

Contrasting previous evidence on choking under pressure in tennis (Cohen-Zada et al., 2017; Paserman, 2023), penalty kicks in football, and free throws in the NBA (Böheim et al., 2019; Cao et al., 2011; Toma, 2017), we find players tend to excel in the critical phases of a game. However, previous evidence is mixed (Ferraresi & Gucciardi, 2021; Hill et al., 2010; Savage & Torgler, 2012), choking during free throws appears to be mainly occurring during the last seconds of very tight games (Goldschmied et al., 2022), and some studies as well find increased performance effects under pressure, e.g., in handball (Bühren & Gabriel, 2023) and baseball (Jane, 2022). As a potential factor contributing to our findings, basketball is a physically demanding sport and unlike NHL players or MLB pitchers who rotate in shifts, top NBA players are in action for most of the game. Hence, NBA players need to manage their energy carefully and it reasonable to assume that the best players can reserve their peak performance during clutch time (Silver, 2013).

As a next step to further investigate the relationship between productivity and compensation, we compute the performance summary statistics by salary level in Table 2.

As expected from a performance-pay industry, Table 2 shows a positive relationship between NBA players' salaries and their performance. Moreover, salary is also linked to the ability to increase performance under pressure. In particular, the bottom 10 % of players, ranked by salary, not only have the lowest HP and LP performance, but also show the smallest difference in HP-LP performance. With a mean value of −0.05, the difference is negative, showing that the players with the lowest salaries are not able to handle pressure well and cannot improve their performance when it counts most. However, both HP and LP performance, as well as the HP-LP performance difference, steadily increase with salary. Moreover, we find HP performance to increase more strongly with salary than LP performance, suggesting that the ability to excel under pressure is a valued employee characteristic.

4. Regression results

4.1. Baseline results

Table 3 presents the regression results based on the empirical model described in equation (1) with and without including team-season fixed effects.

Table 3 confirms previous empirical findings concerning the impact of standard wage regression controls in professional sports markets: age and its squared value (also reflecting player experience) are both significantly different from zero, indicating a positive but concave relationship between age and compensation. Likewise, we find a positive significant effect for All-Star status and a negative significant effect for draft position. While we do not find significant effects for player height and position, our results show a salary premium for ambidextrous players. Moreover, our analysis shows that white players on average receive a significantly higher salary compared to black players; hence, similar to findings in other industries in the US (Laouénan, 2017), our results indicate the prevalence of a positive bias towards White employees. In this context, Following Becker (1957), labor market discrimination can result from consumer, employer, and coworker discrimination. In particular, Becker's theory of segregation states that employers can increase profits by accounting for potential customer discrimination (Becker, 1957). However, unlike consumer discrimination, employer discrimination is likely to reduce profits in competitive labor markets, and, given that workers are mobile in the long run, coworker discrimination likely vanishes over time due to employee self-sorting. It is therefore commonly assumed that employer discrimination does not last in competitive labor markets. As a result, consumer discrimination is more likely to be the source of persistent discrimination than employer or coworker discrimination (Maennig & Mueller, 2022; Principe & Van Ours, 2022). However, this paper's research design does not allow us to examine how different potential sources of racial discrimination are individually contributing to the apparently existing salary premium for White employees.

Considering performance effects, the results in Table 3 are in line with our descriptive analysis and show that players' consecutive-season compensation significantly increases with their current-season performance in LP situations. We further find that a greater HP-LP performance difference significantly increases a player's salary, irrespective of including controls or team-season fixed effects. Moreover, in model (4) we exclude rookies from the sample because their contracts are not openly negotiated; their salaries are primarily determined by their position in the NBA draft. To this end, we collected data on rookies from basketball-reference.com and removed them from the sample, resulting in a "no rookies" subsample with 4,237 (91 % of full sample) observations. Supporting these considerations, the corresponding LP and HP-LP effects remain significant and their magnitudes increase both by approximately 10 % to 2.041 and 0.011, respectively. With respect to our semi-log regression specification, an increase by one unit in a player's HP-LP performance difference translates to a 0.1 % increase in salary (model 3). The corresponding effect for a player's LP performance equates to 6.23 % ($= 1 - e^{1.829}$). Hence, although of relatively small magnitude, our results suggest that players are rewarded for

Table 2
Mean values for high- and low-pressure performance by player salary.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tau = 0.1–0$	$\tau = 0.25–0.1$	$\tau = 0.5–0.25$	$\tau = 0.75–0.5$	$\tau = 0.9–0.75$	$\tau = 1–0.9$
LP performance	0.164	0.169	0.193	0.224	0.269	0.331
	(0.154)	(0.130)	(0.102)	(0.115)	(0.089)	(0.106)
HP performance	0.159	0.297	0.303	0.503	0.593	0.651
	(4.253)	(4.972)	(2.575)	(2.074)	(1.733)	(0.806)
HP − LP performance	−0.005	0.128	0.111	0.279	0.324	0.320
	(4.236)	(4.971)	(2.568)	(2.071)	(1.732)	(0.796)
Minimum salary	51,013	974,563	1,663,660	3,903,000	8,152,800	14,119,683
Maximum salary	974,204	166,2045	3,902,136	8,140,599	1,4106,400	35,344,988
N	465	697	1,161	1,159	699	465

Note: This table shows mean HP and LP performance by salary level for the lowest 10% (1), the 25%-10% quantile (2), the 50%-25% quintile (3), …, 100%-90% quintile (6). Salaries refer to a player's next season's salary (deflated using 2005 as the base year). Performance measured via the Win Score (see Section 3.2 for details). Standard deviations (in parentheses). Data include 4,646 observations at the player-season level derived from 7,588,492 observations of NBA play-by-play data covering the regular and playoff seasons 2004/05 to 2016/17.

Table 3
High- and low-pressure performance effects on player salary.

	(1)	(2)	(3)	(4)
Low pressure performance	3.122***	1.901***	1.829***	2.041***
	(0.345)	(0.265)	(0.255)	(0.294)
HP minus LP performance	0.011*	0.008*	0.010**	0.011*
	(0.005)	(0.004)	(0.004)	(0.004)
Age (in years)		0.799***	0.804***	0.845***
		(0.045)	(0.045)	(0.05)
Age squared		−0.013***	−0.013***	−0.014***
		(0.001)	(0.001)	(0.001)
All-star player		0.720***	0.768***	0.736***
		(0.061)	(0.062)	(0.067)
Draft position		−0.020***	−0.020***	−0.019***
		(0.001)	(0.001)	(0.001)
Height (in cm)		0.001	0.000	0.000
		(0.004)	(0.004)	(0.004)
Position: Forward		−0.046	−0.061	−0.052
		(0.061)	(0.063)	(0.065)
Position: Guard		0.045	0.016	0.027
		(0.095)	(0.097)	(0.102)
Race: Black-White		0.000	−0.017	0.000
		(0.059)	(0.061)	(0.067)
Race: Other		−0.149	−0.120	−0.168
		(0.299)	(0.343)	(0.379)
Race: White		0.115*	0.095	0.105*
		(0.050)	(0.050)	(0.052)
Shooting hand: Left		0.097	0.125	0.137
		(0.076)	(0.078)	(0.083)
Shooting hand: Both		0.729***	0.735***	0.766***
		(0.045)	(0.154)	(0.173)
Constant		3.081**	2.853**	2.314*
		(0.983)	(0.998)	(1.101)
Team-season FE	No	No	Yes	Yes
Rookies	Yes	Yes	Yes	No
N	4,646	4,646	4,646	4,237
R2	0.142	0.408	0.466	0.449
Adjusted R2	0.141	0.406	0.415	0.391

Note: Data include 4,237 observations at the player-season level derived from 7,588,492 observations of NBA play-by-play data covering the regular and playoff seasons 2004/05 to 2016/17. Dependent variable is the natural logarithm of a player's salary in the next season. Salary is deflated using 2005 as the base year. Performance measured via the Win Score (see Section 3.2 for details). Robust standard errors (in parentheses) clustered at the player level.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

increased performance in HP situations. In light of these results, we have to consider two important aspects of LP and HP situations, respectively. First, LP situations represent the standard game scenario. Second, teams prefer to win games with a large point lead—that is, without experiencing HP game phases. It is therefore to be expected that LP performance is of substantially more importance than HP performance. However, games at stake are decided during clutch time, and our results demonstrate that players who are able to elevate their performance during this critical game phase receive a salary premium.

4.2. The impact of performance on negotiating new contracts

While variation exists in players' salaries from season to season, salaries and potential compensation adjustments in subsequent seasons are largely fixed by the contracts that players initially agreed to—salaries only change substantially when new contracts are negotiated. Consequently, performance effects on compensation should be more pronounced when a player receives a new contract. However, details about contract changes are not publicly available. Moreover, when a player changes teams, he typically does not receive a new contract—their new team simply adopts the terms of the existing, previously negotiated, contract until maturity. Similarly, when a player's contract ends, he does not necessarily change teams; rather, he often negotiates a new contract with his current team, for which he then continues to play. We control for these issues by excluding rookies and restricting our sample to observations preceding significant salary changes—defined as at least 15 % or 20 % variation in the subsequent season. This approach helps mitigating potential noise from pre-existing contract structures. Moreover, free agents should have the greatest ability to negotiate their contracts; we account for this peculiarity by including a binary variable indicating whether a player could negotiate his salary as a free agent (data from spotrac.com) and corresponding interaction effects with LP and HP-LP performance. However, data on free agents (N = 671) are more limited and cover the seasons from 2010/11 to 2016/17.

The corresponding results are reported in Table 4 and, in line with theoretical considerations, show an even stronger impact of a player's HP-LP performance difference. Compared to our baseline results excluding rookies, the HP-LP effect for the 15 % [20 %]

Table 4
High- and low-pressure performance effects on new contract salaries.

	(1)	(2)	(3)	(4)	(5)	(6)
Low pressure performance	1.903***	2.379***	1.777***	2.462***	1.565**	1.707***
	(0.456)	(0.479)	(0.527)	(0.636)	(0.536)	(0.604)
HP minus LP performance	0.023**	0.024**	0.030**	0.032***	0.052**	0.053**
	(0.008)	(0.008)	(0.010)	(0.009)	(0.019)	(0.019)
Free agent					0.446*	0.051
					(0.214)	(0.171)
LP performance × Free agent					0.084	2.108**
					(0.908)	(0.691)
HP minus LP performance × Free agent					−0.038	−0.039
					(0.024)	(0.023)
Age (in years)	0.487***	0.422***	0.482***	0.421***	0.332**	0.238*
	(0.078)	(0.083)	(0.107)	(0.111)	(0.111)	(0.113)
Age squared	−0.008***	−0.007***	−0.008***	−0.007***	−0.006**	−0.005*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
All-star player (current season)	0.841***	0.800***	1.075***	1.014***	1.122***	0.972***
	(0.116)	(0.124)	(0.146)	(0.165)	(0.142)	(0.152)
Draft position	−0.019***	−0.018***	−0.018***	−0.017***	−0.018***	−0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Height (in cm)	0.002	0.003	−0.001	0.000	−0.002	−0.002
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Position: Forward	−0.015	0.000	−0.056	0.019	−0.114	−0.022
	(0.087)	(0.092)	(0.114)	(0.122)	(0.109)	(0.113)
Position: Guard	0.103	0.146	0.046	0.146	−0.034	0.112
	(0.137)	(0.148)	(0.173)	(0.193)	(0.170)	(0.180)
Race: Black-White	0.054	0.014	0.088	0.046	0.096	0.065
	(0.087)	(0.088)	(0.108)	(0.112)	(0.106)	(0.107)
Race: Other	0.128	0.033	0.156	0.020	0.056	−0.103
	(0.348)	(0.332)	(0.455)	(0.425)	(0.437)	(0.388)
Race: White	0.168*	0.129	0.209*	0.199*	0.188	0.170
	(0.073)	(0.077)	(0.096)	(0.099)	(0.096)	(0.098)
Shooting hand: Left	0.146	0.158	0.140	0.124	0.097	0.042
	(0.104)	(0.116)	(0.146)	(0.160)	(0.139)	(0.149)
Shooting hand: Both	0.717*	0.623	0.820*	0.702	0.684*	0.502
	(0.359)	(0.357)	(0.363)	(0.362)	(0.324)	(0.320)
Constant	7.712***	8.454***	7.860***	8.521***	10.384***	11.994***
	(1.513)	(1.59)	(1.980)	(2.038)	(3.184)	(3.178)
Team-season FE	Yes	Yes	Yes	Yes	Yes	Yes
Rookies	No	No	No	No	No	No
Seasons	2004/5–2016/17	2004/5–2016/17	2010/11-2016/17	2010/11–2016/17	2010/11–2016/17	2010/11–2016/17
Min. salary change	15 %	20 %	15 %	20 %	15 %	20 %
N	1,783	1,652	1,078	1,008	1,078	1,008
R^2	0.472	0.477	0.462	0.474	0.49	0.516
Adjusted R^2	0.32	0.312	0.321	0.324	0.354	0.376

Note: Data include 4,237 observations (no rookies) at the player-season level derived from NBA play-by-play data covering the regular and playoff seasons 2004/05 to 2016/17. Dependent variable is the natural logarithm of a player's salary in the next season. Salary is deflated using 2005 as the base year. Performance measured via the Win Score (see Section 3.2 for details). Robust standard errors (in parentheses) clustered at the player level. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

salary-change sample (model 1 and 2) remains significant and increases from 0.011 to 0.023 [0.024]. The corresponding effects for the more recent seasons (model 3 and 4) are higher when compared to the full sample. While finding a stronger general HP-LP effect when accounting for free agents (model 5 and 6), we do not find any significant additional effect on the HP-LP performance premium. However, the free agent binary is positive and significant for the 15 % salary-change sample and the interaction effect between the free-agent binary and LP performance is positive and significant for the 20 % salary-change sample, indicating that free agents benefit from their increased leverage in negotiating their contracts. Moreover, we control for potential noise introduced by players who do not have a lot of HP experience by restricting our sample to players who at least have 48 min (corresponding to one game) of HP playing time; the corresponding results are robust and substantiate our previous findings (see Appendix, Section 3).

With respect to our control variables, the white player premium is not significant in model (2) but it is significant and larger than the corresponding baseline effect for the more recent seasons (model 3 and 4). For the same period, and accounting for free agents (model 5 and 6), the effect for white players is not significant anymore. The remaining coefficient estimates reaffirm the results from our baseline regressions.

4.3. Robustness tests and extended analysis

Furthermore, we conduct several robustness checks. First, as an alternative to the Win Score measure, we use the Plus-Minus rating, another well-known and established overall performance measure in various sports (Kahane et al., 2013; Schmidt, 2021). Second, we change the HP criterion in terms of minutes—from the final 5 minutes of a game to the final 4 and the final 6 minutes of the fourth quarter (plus overtime) if neither team is ahead by more than 5 points. Third, we change the HP criterion in terms of the point difference between teams—from the final 5 minutes of the fourth quarter (plus overtime) of a game if neither team is ahead by more than 5 points to the final 5 minutes of the fourth quarter (plus overtime) of a game if neither team is ahead by more than 4 points and 6 points. The corresponding results confirm our main findings and can be consulted in the Appendix, Section 3.

Last, securing a new contract—whether lucrative or not—is not the only possible outcome for a player. In the worst-case scenario, a player may fail to maintain or renew his contract, resulting in his departure from the NBA. Complementing our analysis, we investigate this issue by assessing the impact of LP and HP-LP performance on player exit from the league. Instead of using a player's salary of the next season as dependent variable, we specify a binary variable indicating a player's final NBA season (with $y = 1$ for a player''s last season). We further investigate samples that are restricted by player age (older than 40, 35, and 30 years) to distinguish between players who are unable to secure new NBA contracts and those who are retiring naturally. For both linear and logistic regressions, our results confirm an expected inverse relationship between LP performance and the probability of league departure. In contrast, we do not find any significant HP-LP effects, suggesting that a player's NBA exit probability is not substantially affected by his performance under pressure (see Appendix, Section 5).

5. Conclusion

This paper investigates the extent to which performance differences in low- and high-pressure situations impact employee compensation. Exploiting professional sports markets as a natural laboratory, we base our empirical analysis on a large NBA panel dataset derived from player salary data combined with aggregated play-by-play data. The benefits are twofold. First, the sports setting allows us to use "clutch time"—the final minutes of a game when the outcome is at stake and performance pressure is at the highest level—as an objective criterion by which to measure performance pressure. Second, the highly granular play-by-play data allow us to process individual performance metrics and consolidate them into an overall performance measure for both high- and low-pressure situations.

Our central contribution is to show that employees who can elevate their performance during critical work phases receive a salary premium, whereas those who underperform in such high-pressure phases are financially penalized. Hence, our results suggest that the NBA labor market is efficient when it comes to compensating players for superior performance under pressure. If our analysis did not find such a significant relationship, such players would be undervalued. Underlining the elite caliber of basketball players competing in the NBA, on average, overall performance does not usually decline during clutch time. Instead, some players can maximize their effort when a game outcome is on the line, resulting in better performance during high- compared to low-pressure situations. However, the ability to thrive under pressure is directly linked to compensation. Players at the lower end of the salary distribution tend to perform at a lower level than higher-paid players, regardless of pressure levels, but their performance deteriorates in high-pressure game phases. Higher-earning players exhibit superior performance in both low- and high-pressure scenarios; unlike lower-earning players, they possess the ability to excel under pressure and reserve their peak-performance during the most critical phases of a game. However, it is important to acknowledge that improved performance under pressure is likely affected by star status and the Mathew effect, sunk costs in managerial decisions, peer effects and expectations, and other social factors that might contribute to systematic differences in players' career success.

Overall, our analysis contributes to the literature about the potential effects of pressure on productivity by showing a direct link between compensation and performance under different pressure levels. In particular, we find that excelling under pressure is a highly esteemed ability in employees. Demonstrating the value of sports data for management and economics, our analysis provides important insights into the relationship between compensation and performance under pressure, a relationship that had previously been elusive. Nonetheless, given the inherent pressure associated with performance-dependent pay structures, our findings may be more pertinent to industries with high-pressure working environments than those characterized by low performance pressure. Against this backdrop, future research on the effects of productivity under pressure on compensation for different types of workers and employment sectors is needed to broaden our knowledge of the benefits and risks associated with performance-dependent compensation schemes.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.joep.2025.102807.

References

Ariely, D., Gneezy, U., Loewenstein, G., & Mazar, N. (2009). Large stakes and big mistakes. *Review of Economic Studies, 76*(2), 451–469.
Baktash, M. B., Heywood, J. S., & Jirjahn, U. (2022). Worker stress and performance pay: German survey evidence. *Journal of Economic Behavior & Organization, 201*, 276–291.
Barnes, V., Potter, E. H., & Fiedler, F. E. (1983). Effect of interpersonal stress on the prediction of academic performance. *Journal of Applied Psychology, 68*(4), 686–697.
Baumeister, R. F. (1984). Choking Under Pressure: Self-Consciousness and Paradoxical Effects of Incentives on Skillful Performance.
Baumeister, R. F., & Steinhilber, A. (1984). Paradoxical effects of supportive audiences on performance under pressure: The home field disadvantage in sports championships. *Journal of Personality and Social Psychology, 47*(1), 85.
Becker, G. S. (1957). *The economics of discrimination: An economic view of racial discrimination*. University of Chicago Press.
Beilock, S. L., & Carr, T. H. (2001). On the fragility of skilled performance: What governs choking under pressure? *Journal of Experimental Psychology: General, 130*(4), 701.
Beilock, S. L., & Gray, R. (2007). Why do athletes choke under pressure?. In *Handbook of Sport Psychology* (3rd ed., pp. 425–444). John Wiley & Sons Inc.
Berri, D., Schmidt, M., & Brook, S. (2006). *The wages of wins*. Stanford University Press.
Berri, D. J., & Krautmann, A. C. (2006). Shirking on the court: Testing for the incentive effects of guaranteed pay. *Economic Inquiry, 44*(3), 536–546.
Beus, J. M., Jarrett, S. M., Taylor, A. B., & Wiese, C. W. (2014). Adjusting to new work teams: Testing work experience as a multidimensional resource for newcomers. *Journal of Organizational Behavior, 35*(4), 489–506.
Böheim, R., Grübl, D., & Lackner, M. (2019). Choking under pressure – Evidence of the causal effect of audience size on performance. *Journal of Economic Behavior & Organization, 168*, 76–93.
Booth, A. L., & Frank, J. (1999). Earnings, productivity, and performance-related pay. *Journal of Labor Economics, 17*(3), 447–463.
Booth, A. L., & Nolen, P. (2022). Gender and Psychological Pressure in Competitive Environments: A Laboratory-based Experiment. *Economica, 89*, S71–S85.
Buckert, M., Schwieren, C., Kudielka, B. M., & Fiebach, C. J. (2017). How stressful are economic competitions in the lab? An investigation with physiological measures. *Journal of Economic Psychology, 62*, 231–245.
Bühren, C., & Gabriel, M. (2023). Performing best when it matters the most: Evidence from professional handball. *Journal of Quantitative Analysis in Sports, 19*(3), 185–203.
Bühren, C., Gschwend, M., & Krumer, A. (2024). Expectations, gender, and choking under pressure: Evidence from alpine skiing. *Journal of Economic Psychology, 100*, Article 102692.
Bühren, C., & Steinberg, P. J. (2019). The impact of psychological traits on performance in sequential tournaments: Evidence from a tennis field experiment. *Journal of Economic Psychology, 72*, 12–29.
Cahlíková, J., Cingl, L., & Levely, I. (2020). How stress affects performance and competitiveness across gender. *Management Science, 66*(8), 3295–3310.
Cao, Z., Price, J., & Stone, D. F. (2011). Performance under pressure in the NBA. *Journal of Sports Economics, 12*(3), 231–252.
Célérier, C., & Vallée, B. (2019). Returns to talent and the finance wage premium. *Review of Financial Studies, 32*(10), 4005–4040.
Chandra, A. (2000). Labor-market dropouts and the racial wage gap: 1940–1990. *American Economic Review, 90*(2), 333–338.
Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annu. Rev. Psychol.,, 55*(1), 591–621.
Clarke, P., Sheffield, D., & Akehurst, S. (2020). Personality predictors of yips and choking susceptibility. *Frontiers in Psychology, 10*, 2784.
Cohen-Zada, D., Krumer, A., Rosenboim, M., & Shapir, O. M. (2017). Choking under pressure and gender: Evidence from professional tennis. *Journal of Economic Psychology, 61*, 176–190.
Cortes, G. M. (2016). Where have the middle-wage workers gone? A study of polarization using panel data. *Journal of Labor Economics, 34*(1), 63–105.
DeCaro, M. S., Thomas, R. D., Albert, N. B., & Beilock, S. L. (2011). Choking under pressure: Multiple routes to skill failure. *Journal of Experimental Psychology: General, 140*(3), 390.
Deutscher, C., Frick, B., & Prinz, J. (2013). Performance under pressure: Estimating the returns to mental strength in professional basketball. *European Sport Management Quarterly, 13*(2), 216–231.
Deutscher, C., Gürtler, O., Prinz, J., & Weimar, D. (2017). The Payoff To Consistency in Performance. *Economic Inquiry, 55*(2), 1091–1103.
Dohmen, T. (2008). Do professionals choke under pressure? *Journal of Economic Behavior & Organization, 65*(3–4), 636–653.
Dohmen, T., & Falk, A. (2011). Performance pay and multidimensional sorting: Productivity, preferences, and gender. *American Economic Review, 101*(2), 556–590.
Essl, A., & Jaussi, S. (2017). Choking under time pressure: The influence of deadline-dependent bonus and malus incentive schemes on performance. *Journal of Economic Behavior & Organization, 133*, 127–137.
Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion, 7*(2), 336.
Falk, A., & Ichino, A. (2006). Clean evidence on peer effects. *Journal of Labor Economics, 24*(1), 39–57.
Feri, F., Innocenti, A., & Pin, P. (2013). Is there psychological pressure in competitive environments? *Journal of Economic Psychology, 39*, 249–256.
Ferraresi, M., & Gucciardi, G. (2021). Who chokes on a penalty kick? Social environment and individual performance during Covid-19 times. *Economics Letters, 203*, 1–5.
Fonti, F., Ross, J.-M., & Aversa, P. (2023). Using sports data to advance management research: A review and a guide for future studies. *Journal of Management, 49*(1), 325–362.
Franceschelli, I., Galiani, S., & Gulmez, E. (2010). Performance pay and productivity of low-and high-ability workers. *Labour Economics, 17*(2), 317–322.
Gardner, H. K. (2012). Performance pressure as a double-edged sword: Enhancing team motivation but undermining the use of team knowledge. *Administrative Science Quarterly, 57*(1), 1–46.
Goldschmied, N., Raphaeli, M., Moothart, S., & Furley, P. (2022). Free throw shooting performance under pressure: A social psychology critical review of research. *International Journal of Sport and Exercise Psychology, 20*(5), 1397–1415.
González-Díaz, J., Gossner, O., & Rogers, B. W. (2012). Performing best when it matters most: Evidence from professional tennis. *Journal of Economic Behavior & Organization, 84*(3), 767–781.
Guvenen, F., Karahan, F., Ozkan, S., & Song, J. (2021). What do data on millions of US workers reveal about lifecycle earnings dynamics? *Econometrica, 89*(5), 2303–2339.
Hall, S., Szymanski, S., & Zimbalist, A. S. (2002). Testing causality between team performance and payroll: The cases of Major League Baseball and English soccer. *Journal of Sports Economics, 3*(2), 149–168.
Harb-Wu, K., & Krumer, A. (2019). Choking under pressure in front of a supportive audience: Evidence from professional biathlon. *Journal of Economic Behavior & Organization, 166*, 246–262.

Hickman, D. C., & Metz, N. E. (2015). The impact of pressure on performance: Evidence from the PGA TOUR. *Journal of Economic Behavior and Organization, 116*, 319–330.
Hill, D. M., Hanton, S., Matthews, N., & Fleming, S. (2010). Choking in sport: A review. *International Review of Sport and Exercise Psychology, 3*(1), 24–39.
Jane, W.-J. (2022). Choking or excelling under pressure: Evidence of the causal effect of audience size on performance. *Bulletin of Economic Research, 74*(1), 329–357.
Janssen, O. (2001). Fairness perceptions as a moderator in the curvilinear relationships between job demands, and job performance and job satisfaction. *Academy of Management Journal, 44*(5), 1039–1050.
Kahane, L., Longley, N., & Simmons, R. (2013). The effects of coworker heterogeneity on firm-level output: Assessing the impacts of cultural and language diversity in the National Hockey League. *Review of Economics and Statistics, 95*(1), 302–314.
Kahn, L. M. (2000). The Sports Business as a Labor Market Laboratory. *Journal of Economic Perspectives, 14*(3), 75–94.
Keefer, Q. (2021). Sunk costs in the NBA: The salary cap and free agents. *Empirical Economics, 61*(6), 3445–3478.
Keefer, Q. A. (2017). The sunk-cost fallacy in the National Football League: Salary cap value and playing time. *Journal of Sports Economics, 18*(3), 282–297.
Kocher, M. G., Schindler, D., Trautmann, S. T., & Xu, Y. (2019). Risk, time pressure, and selection effects. *Experimental Economics, 22*, 216–246.
Laouénan, M. (2017). 'Hate at First Sight': Evidence of consumer discrimination against African-Americans in the US. *Labour Economics, 46*, 94–109.
Lazear, E. P. (1998). Hiring risky workers. In *Internal Labour Markets, Incentives and Employment* (pp. 143–158). Springer.
Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review, 90*(5), 1346–1361.
Lindley, J., & Machin, S. (2016). The rising postgraduate wage premium. *Economica, 83*(330), 281–306.
Lindqvist, E. (2012). Height and leadership. *Review of Economics and Statistics, 94*(4), 1191–1196.
Maennig, W., & Mueller, S. Q. (2022). Consumer and Employer Discrimination in Professional Sports Markets: New Evidence from Major League Baseball. *International Journal of Sport Finance, 17*(4), 230–244.
Merton, R. K. (1968). The Matthew effect in science: The reward and communication systems of science are considered. *Science, 159*(3810), 56–63.
Mesagno, C., & Beckmann, J. (2017). Choking under pressure: Theoretical models and interventions. *Current Opinion in Psychology, 16*, 170–175.
Mitchell, M. S., Greenbaum, R. L., Vogel, R. M., Mawritz, M. B., & Keating, D. J. (2019). Can you handle the pressure? The effect of performance pressure on stress appraisals, self-regulation, and behavior. *Academy of Management Journal, 62*(2), 531–552.
Mueller, S. Q., Ring, P., & Fischer, M. (2022). Excited and aroused: The predictive importance of simple choice process metrics. *Journal of Neuroscience, Psychology, and Economics, 15*(1), 31.
Müller, O., Simons, A., & Weinmann, M. (2017). Beyond crowd judgments: Data-driven estimation of market value in association football. *European Journal of Operational Research, 263*(2), 611–624.
Nagler, M., Rincke, J., & Winkler, E. (2023). High-Pressure, High-Paying Jobs? *Review of Economics and Statistics*, 1–45.
Otten, M. (2009). Choking vs. Clutch performance: A study of sport performance under pressure. *Journal of Sport and Exercise Psychology, 31*(5), 583–601.
Paine, N. (2015). *May 11)*. FiveThirtyEight: LeBron May Be The Most Clutch Playoff Shooter Of His Generation.
Paserman, M. D. (2023). Gender differences in performance in competitive environments? Evidence from professional tennis players. *Journal of Economic Behavior & Organization, 212*, 590–609.
Principe, F., & Van Ours, J. C. (2022). Racial bias in newspaper ratings of professional football players. *European Economic Review, 141*, 1–16.
Quirk, J. P., & Fort, R. D. (2018). Pay dirt: The business of professional team sports.
Sanders, S., & Walia, B. (2012). Shirking and "choking" under incentive-based pressure: A behavioral economic theory of performance production. *Economics Letters, 116*(3), 363–366.
Savage, D. A., & Torgler, B. (2012). Nerves of steel? Stress, work performance and elite athletes. *Applied Economics, 44*(19), 2423–2435.
Schmidt, M. B. (2021). Risk and uncertainty in team building: Evidence from a professional basketball market. *Journal of Economic Behavior & Organization, 186*, 735–753.
Shurchkov, O. (2012). Under pressure: Gender differences in output quality and quantity under competition and time constraints. *Journal of the European Economic Association, 10*(5), 1189–1213.
Sieweke, J., Köllner, B., & Süß, S. (2017). The relationship between employees' objective internal and external pay standing and their job performance: A within-person analysis. *Journal of Business and Psychology, 32*, 533–546.
Silver, N. (2013). *June 13)*. New York Times: Heat's Clutch Stats Meet Match in Spurs' Strategy.
Smith, J. (2013). Peers, pressure, and performance at the national spelling bee. *Journal of Human Resources, 48*(2), 265–285.
Staw, B. M., & Hoang, H. (1995). Sunk costs in the NBA: Why draft order affects playing time and survival in professional basketball. *Administrative Science Quarterly*, 474–494.
Toma, M. (2017). Missed shots at the free-throw line: Analyzing the determinants of choking under pressure. *Journal of Sports Economics, 18*(6), 539–559.
Uziel, L. (2007). Individual differences in the social facilitation effect: A review and meta-analysis. *Journal of Research in Personality, 41*(3), 579–601.
Wallace, H. M., Baumeister, R. F., & Vohs, K. D. (2005). Audience support and choking under pressure: A home disadvantage? *Journal of Sports Sciences, 23*(4), 429–438.
Wen, R. (2018). Does racial discrimination exist within the NBA? an analysis based on salary-per-contribution. *Social Science Quarterly, 99*(3), 933–944.
Zajonc, R. B. (1965). Social Facilitation: A solution is suggested for an old unresolved social psychological problem. *Science, 149*(3681), 269–274.