Outcome Bias Under Pressure: Evidence from Managerial Dismissals

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Abstract

Outcome bias refers to the tendency to overweight the observed outcome in evaluations, consequently underestimating the influence of luck. However, observed outcomes frequently trigger performance pressure when they fall short of expectations, potentially reinforcing outcome bias. Using data from European football, we investigate whether managerial dismissal decisions are influenced by luck, operationalized as opponent player injuries, and whether this influence is more pronounced under performance pressure. Our findings reveal that luck significantly impacts dismissal decisions, particularly when performance pressure mounts. Importantly, this amplified outcome bias under performance pressure is predominantly driven by instances of bad luck. These results suggest that the extent of outcome bias has been underappreciated, especially in situations involving bad luck.

Keywords
Outcome Bias, Luck, Performance Pressure, Performance Evaluation, Principal-Agent Setting

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1 INTRODUCTION

Performance evaluation in a principal-agent setting is a complex task. Economists agree that agents (e.g., CEOs) should not be punished or rewarded for factors beyond their control (Holmström, 1979), such as luck – an exogeneous, uncontrollable, and temporary factor (Denrell et al., 2019; Liu & de Rond, 2016; Rubin & Sheremeta, 2016). However, in reality, "rewards for good luck" and "punishments for bad luck" may nevertheless occur. Observed outcomes are usually a function of skill (ability and effort) and exogenous factors (i.e., luck) (Denrell et al., 2019; Liu & de Rond, 2016; Rubin & Sheremeta, 2016), and principals (e.g., the board of directors) tend to underestimate or ignore the role of external or random factors and overweight the observed outcome (Allison et al., 1996; Liu & de Rond, 2016). Thus, principals succumb to an "outcome bias" by rewarding (punishing) agents for good (bad) luck (Baron & Hershey, 1988; Brownback & Kuhn, 2019; Gauriot & Page, 2019).

The tendency to overweight the observed outcome and thus failing to filter out luck in evaluations is widely documented both in experimental studies (Brownback & Kuhn, 2019; Gurdal et al., 2013; König-Kersting et al., 2021) and in the field (Gauriot & Page, 2019; Kausel et al., 2019). However, an often overlooked consideration in the prior literature is that observed outcomes may prompt the emergence of performance pressure when current performance deviates from organizational expectations.

In such a situation, principals are under strong pressure to turn things around and must try to avert potential negative consequences of the performance shortfall. Drawing on insights from distraction theory (Byrne et al., 2015; B. P. Lewis & Linder, 1997) we argue that this outcome-induced performance pressure impairs the capacity to deliberately process information. Since stressful situations can pose a challenge to information processing of individuals and groups (Staw et al., 1981) our underlying reasoning is grounded in the idea that principals may make more accurate decisions under low pressure but more biased ones under high-pressure (Byrne et al., 2015).

Our core argument builds on that outcome-induced performance pressure increases the overweighting of observed outcomes in evaluations. Thus, we propose that performance pressure accentuates the consideration of luck in evaluation decisions. Moreover, since luck can manifest as either good or bad (Liu & de Rond, 2016) we argue that both the tendency to penalize agents for bad luck and to reward them for good luck is accentuated when performance pressure mounts. Thereby, we aim for a better, more comprehensive and accurate understanding of the true impact of outcome bias.

By testing our predictions in the context of European football, we overcome various challenges associated with empirical examinations of how economic actors act in evaluation decisions (Gauriot & Page, 2019; Lefgren et al., 2015). Professional sports is a high-stakes environment and an ideal setting to test hypotheses about sophisticated economic actors (Kahn, 2000; Lefgren et al., 2015; Lefgren et al., 2019). First, focusing on the high-stakes decision whether to dismiss the head coach in European football represents an evaluation that receives considerable domestic and worldwide media attention, bears substantial financial consequences, and triggers the risk of reputational damage for both the decision-making principals (i.e., club boards) and the agent (i.e., the coach) (van Ours & van Tuijl, 2016). Second, weekly performance signals allow to align skill and luck components more precisely to turnover decisions in contrast to less frequent available quarterly or annual performance data. Moreover, embellishment of results is unlikely in football compared to earnings-based measurements (d'Addona & Kind, 2014). Third, match outcomes in football are heavily influenced by luck and may not reliably reflect team performance on the pitch (Brechot & Flepp, 2020; Wunderlich et al., 2021). Consequently, observed outcomes encompass a non-neglectable luck component.

Fourth, our setting allows to overcome the typical measurement difficulties for luck by employing key opponent injuries as a novel source of luck. Notably, while injury-related absences of key focal players may not be completely uninformative of the coach's ability, injury-related absences of key opponent players represent a source of exogenous performance boosts for the focal team and coach.[1] We proxy luck by accumulating and median-adjusting key opponent injuries and distinguish bad luck (good luck) by determining the extent to which luck is negative (positive).[2] Finally, the context

[1] We acknowledge that key opponent injuries only capture a specific aspect of luck in European football. Brechot and Flepp (2020) outline that football is a low-scoring game in which winning or losing is sometimes decided by one single goal and, thus, the game is heavily influenced by randomness. Therefore, further sources of luck we do not capture certainly exist.

[2] Doing this provides an additional advantage of our setting. While previous field studies on outcome-biased decisions predominantly focused on quasi-experimental regression discontinuity designs to proxy exogeneous luck (Flepp & Meier, 2023; Gauriot & Page, 2019; Kausel et al., 2019; Lefgren et al., 2015; Meier et al., 2022; Meier, Flepp, & Franck, 2023; Meier, Flepp, & Oesch, 2023) we are able to quantify the extent of luck.

of European football allows a simple distinction of low and high pressure situations. Our setting permits to proxy team-specific variations in performance pressure by calculating the difference of the league table rank to preseason targets. We utilize the threat of relegation to capture the highest pressure, which also entails significant financial consequences (Dios Tena & Forrest, 2007; Moliterno et al., 2014).

Consistent with our predictions the empirical findings reveal that principals are more likely to fall prey to outcome bias in situations in which observed outcomes trigger performance pressure. Principals evaluate agents based on luck, particularly when performance pressure mounts. These effects, however, are primarily driven by bad luck. Thus, agents get particularly penalized for bad luck when principals increasingly face performance pressure.

Our findings first and foremost contribute to the literature on outcome bias by emphasizing and providing statistical evidence that ignoring observed outcomes' impact on performance pressure leads to an underappreciation of outcome bias. By focusing and estimating the impact of performance pressure on outcome biased evaluations in European football, we add field evidence that supports the importance of distraction theories in cognitive decision-making. Furthermore, we contribute to the broader literature on the influence of luck and its effect on decision-makers (Liu & de Rond, 2016). Finally, we also contribute to the literature on coach dismissals in European football by highlighting that coaches are dismissed for factors beyond their control. Methodologically, we developed a novel measurement for luck in European football.

The remainder of this paper is structured as follows. Section 2 presents an overview on the existing literature and derives testable hypotheses. Section 3 describes the data and explains the estimation strategy whereas Section 4 depicts the results of our empirical analyses and employs alternative specifications. We discuss the implications of our results in Section 5 and conclude the paper in Section 6.

2 RELATED LITERATURE AND HYPOTHESES

2.1 Outcome bias in principal-agent evaluations

Outcome bias is a widespread, empirically examined phenomenon that occurs when individuals overweight the informativeness of outcomes in evaluations (Baron & Hershey, 1988). Since taking into account observed outcomes is not generally considered outcome bias[3], cognitive distortion only occurs when inferences about ability are based on outcomes that were influenced by exogenous factors outside an individual's control (Baron & Hershey, 1988). In such situations, the outcome is partly uninformative and obscures valuable information about an agent.

Falling prey to outcome bias thus describes the inverse fallacy that good outcomes follow from good decisions and bad outcomes result from bad decisions. Outcomes usually consist of a skill (ability and effort) component and exogeneous factors (luck) (Denrell et al., 2019; Rubin & Sheremeta, 2016), and agents' successes or failures are driven by both actions and random circumstances (Gauriot & Page, 2019). However, since disentangling luck and skill is challenging (Budescu & Bruderman, 1995), individuals tend to ignore external factors by not considering that bad decisions may result in good outcomes and good decisions in bad ones (Allison et al., 1996). Thus, in principal-agent evaluations, outcome-biased evaluations result from a misattribution of luck for skill, fostering the biased belief that lucky agents are more hardworking than unlucky ones (Brownback & Kuhn, 2019).

The seminal work of Baron and Hershey (1988) investigates outcome bias among students evaluating medical procedures. Despite knowing the predetermined success probability of a medical procedure, students assessed the decisions more favorably after successful procedures than after unsuccessful ones. Subsequently, the existence of outcome bias has been documented in numerous experimental and field studies, including principal-agent settings.[4]

Principals tend to rate the competence of an agent more positively (negatively) when outcomes are positive (negative), regardless of exogenous factors that have influenced the outcome. In a role-play

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[3] For example, Lefgren et al. (2019) focus on circumstances in the NBA in which performance outcomes contain relevant information about an agent and thus, are arguably in line with optimal contracting.

[4] Empirical literature also reports evidence of outcome bias in contexts other than principal-agent settings, such as for example, self-evaluations (Lefgren et al., 2015; Meier et al., 2022; Meier, Flepp, & Franck, 2023), independent third-party evaluations (Brownback & Kuhn, 2019; Kausel et al., 2019), or betting markets (Flepp et al., 2023).

experiment with students as sales managers, the sales manager considered only the outcome when evaluating salespeople, independent of the appropriateness of the decision by salespeople (i.e. choosing the recommended vs. not recommended option by the sales department) (Marshall & Mowen, 1993). When agents choose between safe choices or a lottery, agents are punished based on the outcome of the lottery, although being an event beyond their control (Gurdal et al., 2013). Crucially, outcome bias even occurs in transparent settings and agents are punished for bad luck although both effort and luck are perfectly observable (Brownback & Kuhn, 2019). In the context of predefined probabilities of success in risky and non-risky financial investment decisions, principals reward positive outcomes even if they initially did not agree with the agent's investment strategy (König-Kersting et al., 2021).

Field evidence of outcome bias in principal-agent settings mostly stems from the sports context. Examining within-player differences in European football, Gauriot and Page (2019) find that principals, i.e. coaches, overly reward good luck in performance outcomes. In the match following lucky successes (i.e., scoring a goal in the quasi-arbitrary outcome whether shots that hit the post from a similar distance result in a goal) players receive more playing time and have a higher probability to be fielded and to be selected to the starting lineup.

In line with prior literature, we thus argue that principals erroneously perceive agents experiencing higher levels of luck as more capable. Consequently, we propose that agents are likely to be rewarded in instances of higher levels of luck. In the context of our high-stakes evaluation decision of managerial dismissal, we state the following hypothesis:

Hypothesis 1a: *A higher level of luck is associated with a decreased probability of managerial dismissal.*

As luck has a dual nature by being either good or bad (Liu & de Rond, 2016), good luck captures beneficial events leading to desirable outcomes, while bad luck is associated with unpleasant outcomes (Baumeister et al., 2001). Applied to the organizational context, positive events beyond an agent's and an organization's control may be considered good luck, whereas negative events imply bad luck (Amore & Schwenen, 2022). Since bad luck is more likely to lead to worse performance outcomes, we assume that principals erroneously perceive agents experiencing bad luck as less skilled and those experiencing good luck as highly capable. Consequently, we argue that agents are penalized for bad luck and rewarded for good luck.

Hypothesis 1b: *A higher level of bad luck is associated with an increased probability of managerial dismissal.*

Hypothesis 1c: *A higher level of good luck is associated with a decreased probability of managerial dismissal.*

2.2 Moderating role of performance pressure

The extant literature on outcome bias typically looked at how an observable outcome influences principals' evaluation of an agent. Thereby, the focus has been only on one side of the coin. The neglected second side, however, concerns the influence of observable outcomes on performance pressure which has been, by and large, overlooked. Since organizations are driven by different expectations such as meeting sales targets, or in our context winning the league title or qualifying for European competitions (Brechot & Flepp, 2020; Moliterno et al., 2014), observed outcomes relative to organizational expectations may play a crucial role in determination whether current performance is deemed satisfactory and thus, whether principals face performance pressure. The effect of such outcome-induced performance pressure on outcome biased evaluations has yet to be explored.

We start by asserting that performing below organizational expectations leads to the emergence of performance pressure. Performance pressure generally describes a situation in which there is a heightened importance of performing well (Baumeister, 1984). Building upon this, Gardner (2012) further characterizes performance pressure as a situation under heightened scrutiny that demands high performance due to significant consequences of failing to meet expectations, such as in a sample of consulting and audit teams the threat of job termination if clients are not satisfied.[5] Importantly, the urgency to improve performance due to potential negative consequences weights heavily on individuals and creates pressure (Mitchell et al., 2019). The experience of such performance pressure then demands

[5] Gardner (2012) further identifies shared accountability as an important interrelated factor creating performance pressure on teams. Principals in our settings are club boards, which are likely to be comprised of multiple individuals. However, the underlying reasoning would remain similar, even if club boards were composed of one single individual.

responses to tackle potential threats stemming from, for example, failing to meet expected performance standards (Spoelma, 2022). Hence, a situation where observed outcomes fall short of organizational expectations captures a performance pressure scenario in line with common understandings of performance pressure.

Although performance pressure can positively influence task performance through motivational factors (Eisenberger & Aselage, 2009; Gardner, 2012), understanding its effect on potentially biased decision-making in a high-stakes environment requires focusing on the influence performance pressure has on cognitive capacities (Byrne et al., 2015; B. P. Lewis & Linder, 1997). Insights of distraction theory (e.g., Byrne et al., 2015; B. P. Lewis & Linder, 1997) imply that performance pressure impairs task performance by increasing the cognitive load due to increased distraction and thus, preoccupation with other thoughts. Certain stimuli, such as performance pressure, decrease task performance by redirecting the attentional focus away from task-relevant information. The distraction, however, can arise from both external and internal factors. For instance, internal anxiety potentially resulting from performance pressure drives attention away from the primary tasks and impairs performance since individuals are preoccupied with other thoughts (B. P. Lewis & Linder, 1997).

We thus build on the premise that performance pressure creates mental distractions which may impair cognitive abilities (Byrne et al., 2015). Indeed, acute stressful situations can restrict information processing of individuals and groups by narrowing down attention and simplifying information (Staw et al., 1981) and the cognitive ability to perform complex tasks diminishes under scrutiny (Ellis, 2006). Similarly, time constraints and uncertainty impair the capacity to systematically and deliberately process information (Kahneman, 2003, 2011; Soll et al., 2015) and the demand for quick actions redirects the cognitive system to find fast solutions (Dreu, 2003; Finucane et al., 2000; Gilbert & Hixon, 1991; Payne et al., 1993; Soll et al., 2015). Thus, under performance pressure, focus shifts from task-relevant to task-irrelevant information are likely (B. P. Lewis & Linder, 1997).

The increased tendency to consider irrelevant information under performance pressure has, however, important implications for outcome-biased evaluations. As performance pressure increases, decision-making principals may assign greater importance to observed outcomes. Consequently, principals tend to overweight observed outcomes more in high-pressure than they would in low-pressure situations. Indeed, when individuals' cognitive abilities are not encumbered by situational demands, outcome-biased inferences should be less likely (Allison et al., 1996). Thus, by reducing cognitive resources, performance pressure may increase principals' tendency to fall prey to outcome bias in evaluations. Consequently, principals facing higher performance pressure are more inclined to consider luck in their evaluations.[6] The following hypothesis reflects this tendency in the high-stakes evaluation decision of managerial dismissal:

Hypothesis 2a: *The negative relationship between luck and the probability of managerial dismissal is accentuated under higher levels of performance pressure.*

Regarding the effect performance pressure on the consideration of bad luck and good luck, we argue that bad luck potentially increases (unjustified) outcome-induced performance pressure. This, in turn, may result in an overemphasis on bad luck in observed outcomes and consequently, an accentuated probability of managerial dismissal in instances of bad luck and performance pressure.

Hypothesis 2b: *The positive relationship between bad luck and the probability of managerial dismissal is accentuated under higher levels of performance pressure.*

Conversely, if outcomes, though below expectations, involve good luck, the probability of too mild performance pressure increases, leading to a decreased probability of managerial dismissal. Since performance pressure nonetheless leads to preoccupation with other thoughts, principals become too lenient by shifting the focus from relevant information to irrelevant information, such as good luck.

Hypothesis 2c: *The negative relationship between good luck and the probability of managerial dismissal is accentuated under higher levels of performance pressure.*

[6] We refer to the principals as exhibiting outcome bias. While decision-makers may appease various stakeholders, performance pressure may additionally be exercised by stakeholders. However, this does not contradict our reasoning. Since distraction models (Byrne et al., 2015; B. P. Lewis & Linder, 1997) emphasize that distraction may arise from external, i.e., various stakeholders, or internal, i.e., own anxiety, factors, it is, admittedly, likely that those forces appear in tandem. However, independent of whether theses distraction factors arising from performance pressure are external or internal, the importance is the negative effect these distractions have on cognitive decision-making. Importantly, in both instances, principals are arguably preoccupied with other thoughts.

3 METHODS

3.1 Data and sample

We test our hypotheses using a comprehensive dataset on the top five European football leagues (i.e., Premier League, La Liga, Serie A, Ligue 1, and 1. Bundesliga) between the 2016/2017 and 2020/2021 seasons. We collect various information on players, coaches, and teams from the website www.transfermarkt.com. In particular, we derive team compositions, players' injury histories, starting lineups, corresponding coaches, and historical end-of-season league table standings. We further rely on the website www.kicker.de to receive match week based league table ranks. The primary dataset covers 18,058 team performance observations from 9,029 games[7]. As we discuss below, we identify 149 head coach dismissals and exclude all team-season observations after the first dismissal. Importantly, we exclude all team performance observations that occurred after the first within-season dismissal, resulting in 14,458 team performance observations for our main analysis.

3.2 Variables

3.2.1 Dependent variable

In line with Pieper et al. (2014) and Flepp and Franck (2021), we define within-season coach changes as dismissals if the associated (online) press articles suggest that the turnover was involuntary. Following van Ours and van Tuijl (2016), we ignore dismissals in the first four games. Further, building upon Besters et al. (2016) and Flepp and Franck (2021), we only consider the first within-season coach dismissal[8]. Overall, we registered 149 coach dismissals.

3.2.2 Luck

As per definition, luck has to be independent of the coach's quality as well as external to the coach and team (Liu & de Rond, 2016). Building upon the finding that injury-related absences of key players decrease team performance of the focal team in general (Chen & Garg, 2018; Jedelhauser et al., 2023), we argue that injury-related absences of key opponent players are a source of exogeneous performance boosts that increase the winning chances of the focal team. While injuries of the focal team

[7] Every game appears twice in our analysis, once from the home team perspective and once from the away team perspective.
[8] Our results are robust to the consideration of all dismissals (full sample).

may not be completely uninformative of the coach's ability (e.g., due to intense trainings), opponent injuries are arguably exogeneous to the focal team and coach. Therefore, we assume a team to benefit from luck throughout the season when it gains more advantages from opponent injuries than other teams.

To build our luck measurement we first identify key opponent players by relying on the number of games players have been selected to the starting lineup within a season and team. Coaches aim to start with their strongest players at each position to increase the probability of winning the game and selection to starting lineups captures the relative importance of players (Gauriot & Page, 2019; Lefgren et al., 2015). Key players are thus defined as those who have been selected to the starting lineup in more than 90% of possible games per team and season.[9] We are further aware of 401 within season player changes in the top five leagues. Thus, a player can be considered a key player for two teams within one season if, for example, he changed teams during the winter transfer window. We manually check these players' transfer histories to adjust the number of possible games per player, team, and season. The number of possible games is further reduced by the number of games per team a player missed due to an injury-related absence. We finally identify 829 key players out of information on 4,636 players who have at least once been selected to the starting lineup. From the 829 identified key opponent players, 551 report at least one injury-related absence.

Second, we proceed by aggregating the number of key opponent injuries to the focal team's game level. In particular, we sum up the number of key opponent injuries the focal team profited from until a given game[10] and in a particular season. Basically, we derive the cumulative number of key opponent injuries as a source of exogenous performance boosts. For example, if Arsenal's opponent in round one had two key players injured and the opponent in round two had three key players injured, the cumulative number of key opponent injuries would have a value of five in Arsenal's second game.

[9] While this threshold is arguably somewhat arbitrary, our result do not change when we apply a threshold of 80% of possible games.
[10] We include the focal game.

Third, as previously outlined, every team is naturally expected to profit from key opponent injuries to a certain extent. We thus subtract the median value[11] of the cumulative key opponent injuries per league, season, and games played from the focal team's cumulative number of key opponent injuries to construct our *Luck* measurement. Doing this allows to distinguish team-specific levels of luck relative to the expected values of all teams within a league and season. The advantage of this approach is that the *Luck* variable takes on positive or negative values and does not systematically increase over time.

3.2.3 Bad Luck and Good Luck

To distinguish bad and good luck we rely on the extent our *Luck* measurement is positive or negative. Positive values suggest that teams profited more from key opponent injuries than the median team. Thus, teams with positive values were relatively more lucky. In contrast, negative values indicate that teams could profit less than the general expectation and thus, the teams experienced relatively bad luck. Specifically, we distinguish teams with relatively bad luck from those with relatively good luck by constructing two semi-continuous variables as formally expressed in equation (1). *Bad Luck* equals the absolute value of *Luck* if *Luck* is negative, otherwise zero. *Good Luck* equals *Luck* if *Luck* is greater equal zero, otherwise zero. [12]

$$\begin{gathered} \textit{Bad Luck}: |\textit{Luck}| \text{ if } \textit{Luck} < 0, \text{ zero otherwise} \\ \textit{Good Luck}: \textit{Luck} \text{ if } \textit{Luck} \geq 0, \text{ zero otherwise} \end{gathered} \tag{1}$$

Our luck measurement is valid if it impacts observed outcomes in European football. Table A1 validates that our conceptualization of luck captures exogenous performance boosts. Columns (1) and (2) provide empirical evidence that the number of *Key Opponent Injuries* significantly increase team performance proxied by the *Goal Difference* (column 1) and *Points* won (column 2) in a single game. Crucially, column (3) reveals that the accumulated and median-adjusted *Luck* variable significantly reduces the league table rank. Thus, experiencing relatively more luck leads to better performance. Finally, *Bad Luck* increases the league table rank while *Good Luck* is associated with lower ranks in column (4).[13]

[11] The interpretation of our results remains similar if we take the mean instead. However, we opted for the median as the median is less sensitive to outliers than the mean.
[12] Table A2 presents a real data example to illustrate the construction of our main independent variables.
[13] Please note that in European football high ranks refer to bad performance and low ranks to good performance.

3.2.4 Performance Pressure

One advantage of our settings is the clear distinction between high and low pressure situations based on two different measurements. First, we operationalize performance pressure to be present when performance falls short of organizational expectations. To build the preseason expectations of teams we rely on the approach from the performance feedback literature (Levinthal & March, 1981; Moliterno et al., 2014). Since organizations often build their target based on historical performance (Moliterno et al., 2014) we follow the standard approach of the performance feedback literature (Levinthal & March, 1981) and construct a team's preseason expectations based on the weighted exponential moving average of the team's last season rank and the team's previous historical aspirations (*HAL*) as indicated in equation (2). The intuition about alpha is, that high alphas indicate greater importance of more recent performance outcomes whereas lower alphas increases the importance of more distant outcomes.

$$HAL_t = \alpha \cdot Final\ Rank_{t-1} + (1-\alpha) \cdot HAL_{t-1} \tag{2}$$

We set alpha equals one in our main analysis. Thus, the *HAL* corresponds to a team's final rank in the previous season.[14] To construct the *Performance Pressure* extent measurement we first calculate the rank difference between a team's historical aspirations (*HAL*) and the team's rank (*Rank*) after each match. Negative values of the rank difference thus indicate that teams are below preseason expectations, while positive values are an indication of the extent a team currently overperforms. To construct the *Performance Pressure* variable, however, we multiply the rank difference times minus one. Doing this allows negative values to capture the extent of overperformance and positive ones indicate increasing performance pressure as formally expressed in equation (3).

$$Performance\ Pressure = (HAL - Rank) \cdot (-1) \tag{3}$$

We employ a second measurement of performance pressure which is captured by the threat of relegation. Since relegation is accompanied by massive sporting and economic consequences, it represents the highest form of performance pressure in European football (Dios Tena & Forrest, 2007; Moliterno et al., 2014). To build the variable *Relegation Pressure* we build a dummy variable which equals one if a team's league table standing is in a potential relegation rank, otherwise zero. By doing

[14] Teams that got promoted received the highest possible rank within the league as the final rank in the previous season.

this, we treat the relegation playoff spots existing in certain leagues (i.e., Bundesliga and Ligue 1) as a direct relegation spot.

3.2.5 Controls

Although our *Luck* variable is exogenous, we include several controls. First, as performance outcomes matter for dismissal decisions in general (Bryson et al., 2021; Pieper et al., 2014; van Ours & van Tuijl, 2016) we control for the cumulative percentage of wins a team has achieved including the focal game (*Win Percentage*) (Lefgren et al., 2019)[15]. Second, we control for *Tenure* in days at the current club as the experience of a coach could potentially protect a coach from dismissal (Bryson et al., 2021). Moreover, longer tenure at a club could may facilitate disentangling luck and skill, as club boards become more acquainted with the coach. Third, we control for *Games Played* as coach dismissals may not be equally distributed over the season (Pieper et al., 2014). Indeed, in our sample 67% of the coach dismissals take place in the first half of the season.

Fourth, although key opponent injuries are exogenous, incentives to strategically rest key players before important games could affect key opponent injuries and thus, our luck measurement. Important games, such as UEFA competitions, can create higher incentives to strategically rest key players (Jedelhauser et al., 2023; Kaplan, 2022; T. Peeters, 2018). We thus include a dummy variable capturing whether or not the opponent is still competing in UEFA competitions (*UEFA Period Opponent*). Finally, as the extent to which the focal team benefits from external good (bad) luck might be affected by its own injury-related absences, we control for the median-adjusted cumulative number of key focal player injuries (*Key Focal Injuries*).[16]

Table 1 depicts the summary statistics and correlations of the main variables of interest. The creation of the *Luck* variable is based on the full data sample (18,058 observations), however, descriptive statistics are calculated for the observations included in our main analyses (14,458 observations). Moreover, by occurring in 37.5% versus 11.5% of our team observations, we see that

[15] We calculate the win percentage by dividing the number of wins by the number of games played in the season. Thereby, draws are categorized as losses.
[16] The median is again taken per league, season, and games played.

principals face more often *Performance Pressure* than *Relegation Pressure*. However, this is not surprising since the majority of teams never compete in the relegation zone throughout the season.

Insert Table 1 about here

3.3 Model specification

We test our hypotheses running OLS regressions. OLS estimation to explain a binary outcome is an appropriate choice if the interest is on marginal effects (Wooldridge, 2010; Wulff et al., 2023). Moreover, interpretation of interaction terms in logit models is harder than in OLS models (Hoetker, 2007). In our baseline OLS regression analysis we thus regress the probability of *Coach Dismissal* on *Luck*. We then add our set of controls and account for unobserved but time-constant within-season differences in team quality by adding team-season fixed effects (Flepp & Franck, 2021; van Ours & van Tuijl, 2016). We also include coach fixed effects to control for unobserved, stable coach characteristics. This is crucial to alleviate the potential concern that, while good and bad luck can happen to anyone, certain individuals may have superior strategic responses to luck (de Rond, 2014; Liu & de Rond, 2016). We thus regress coach dismissal on luck (bad and good) as formally expressed in equation (4), where i denotes the game, j the team, k the season, and l the coach. X is a vector of control variables, η contains team-season fixed effects and θ captures coach fixed effects. We adjust for potential serial correlation in panel data by computing standard errors that are clustered at the game level.[17]

$$Coach\ Dismissal_{ijkl} = \beta_0 + \beta_1 \cdot Luck_{ijkl} + \beta X + \eta_{jk} + \theta_l + \varepsilon_{ijkl} \tag{4}$$

We then examine how *Performance Pressure* and *Relegation Pressure* moderate the relationship between *Luck* (*Bad Luck* and *Good Luck*) and the dismissal probability as expressed in equation (5). The term Pressure in the equations is placeholder for either *Performance Pressure* or *Relegation Pressure*.

$$Coach\ Dismissal_{ijkl} = \beta_0 + \beta_1 \cdot Luck_{ijkl} + \beta_2 \cdot Pressure_{ijkl} + \beta_3 \cdot Luck_{ijkl} \cdot Pressure_{ijkl} + \beta X + \eta_{jk} + \theta_l + \varepsilon_{ijkl} \tag{5}$$

[17] Clustering the standard errors at the team level does not change our results.

4 RESULTS

4.1 Main results

Table 2 reports the results to test our hypotheses. Columns (1) and (2) provide support for Hypothesis 1a stating that higher levels of luck decrease the probability of managerial dismissal. In column (1) the *Luck* coefficient is negative and significant (β = -0.00141, p-value < 0.01), implying that coaches of teams with relatively higher levels of luck have a lower probability of being dismissed. Including team-season fixed effects, coach fixed effects, and our set of control variables in column (2) we find a negative and significant effect (β = -0.00179, p-value < 0.05) of luck on the dismissal probability. Importantly, this effect is also of economic relevance. A one standard deviation increase of *Luck* (1.556) decreases the dismissal probability per matchday by 0.28 percentage points, which corresponds to a decrease of the dismissal probability by 28% compared to the average dismissal rate of 0.01 per matchday (column 2).[18]

Disentangling the effects of bad luck and good luck, columns (5) and (6) reveal that the effects of luck on the dismissal probability are mainly driven by bad luck. The baseline estimation in column (5) reports a negative and statistically significant effect of *Bad Luck* on the managerial dismissal probability (β = 0.00273, p-value < 0.05). Including fixed effects and controls, the *Bad Luck* coefficient has a positive and significant effect (β = 0.00437, p-value < 0.05) on the managerial dismissal probability in column (6) while *Good Luck* is negative but remains insignificant (β = -0.0003, p-value > 0.95). We thus find evidence for Hypothesis 1b but lack statistical support for Hypothesis 1c. Regarding the economic relevance of the *Bad Luck* coefficient in column (5), the regression analysis indicates that a one a one standard deviation increase in *Bad Luck* (0.826) corresponds to an increased dismissal probability of approximately 52 % per match day compared to the average dismissal rate. [19]

Insert Table 2 about here

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[18] -0.00179 x 1.556 / 0.10 = 0.279
[19] 0.00437 x 0.826 / 0.10 = 0.529

Estimates in column (3) and column (4) aim to validate our proposition that performance pressure accentuates the consideration of luck in evaluations. Column (3) depicts the result of capturing *Performance Pressure* based on the deviation from current outcomes to preseason expectations. The interaction coefficient of *Performance Pressure* and *Luck* is negative and statistically significant (β = -0.00056, p-value < 0.01). Thus, and in line with Hypothesis 2a, we find statistical support that principals under performance pressure tend to be more outcome-biased in their agent evaluations. Although the coefficient in column (4) is negative and thus, goes in the proposed direction, we do not find a statistically significant moderating effect of *Relegation Pressure* on *Luck* (β = -0.00427, p-value > 0.29).

Our results in columns (7) and (8) reveal that the reinforcing effect of performance pressure on outcome bias in managerial dismissal decisions is particularly pronounced upon principals' responses to bad luck. In column (7), the *Bad Luck* coefficient is still positive and significant (β = 0.00517, p-value < 0.001) while this effect is accentuated when performance pressure mounts, as indicated by the positive and significant interaction coefficient *Performance Pressure x Bad Luck* (β = 0.00154, p-value < 0.001). Similarly, the interaction coefficient *Relegation Pressure x Bad Luck* is also positive and significant (β = 0.02125, p-value < 0.001).

In contrast, our data do not provide statistical support for the reinforcing effect of performance pressure on the consideration of good luck in agent evaluations. Columns (7) and (8) display that both interaction effects Performance *Pressure x Good Luck* (β = 0.00017, p-value > 0.3) and *Relegation Pressure x Good Luck* (β = 0.00655, p-value > 0.2) are positive but remain insignificant. Thus while we find supporting statistical evidence for hypothesis 2b, we fail to find support for hypothesis 2c. Consequently, our results indicate that performance pressure has a reinforcing effect solely in instances of bad luck but not when agents experience good luck.

Figure 1 and Figure 2 further provide graphical evidence of the interaction effects based on the results of column (7) in Table 2. Figure 1 reveals that if bad luck is zero, the dismissal probability is generally higher if performance pressure is higher. This difference, however, becomes larger with higher levels of bad luck. Figure 2 in contrast shows that the difference in the dismissal probability between varying levels of performance pressure does not become much larger as good luck increases.

Summarizing our results, we provide statistical evidence that principals generally tend to fall prey to outcome bias by considering luck in agent evaluations. Higher levels of performance pressure reinforce the considerations of outcomes and thus, accentuates outcome biased evaluations. These results, however, are particularly driven by principals' reaction to agents' bad luck. Consequently, agents particularly get penalized for bad luck when principals are under pressure.

4.2 Alternative specifications

In our main analysis we implicitly assume that coaches receive a new start every season which might be different in reality. We thus estimate coach specific duration models in which the tenure of a coach relates to separate coach-team dyads (van Ours & van Tuijl, 2016).[20] Doing this further allows to compare our results to duration modes, which are frequently used in the sports context (Bryson et al., 2021; Semmelroth, 2022; van Ours & van Tuijl, 2016) but also in the managerial context (Wang et al., 2023). Table 3 reports the results of our right-censored duration analysis based on cox proportional hazard models. The estimations support our previous findings. Luck generally has a negative effect on the dismissal probability, and this effect is mainly driven by bad luck. While the interaction between *Luck* and *Performance Pressure* is significant (p-value < 0.05), we do not find a significant moderation effect of *Relegation Pressure* (p-value > 0.28). Similar to our main results, the positive effect of *Bad Luck* on the dismissal probability is accentuated when principal face both *Performance Pressure* or *Relegation Pressure*.

Insert Table 3 about here

Since our specifications could be sensitive to other operationalization of performance pressure we re-estimate equation (5) relying on three alternative pressure measurements in Table 4. Columns (1) and (4) differ between a low and high pressure situation through a *Performance Pressure Dummy* that equals 1 if teams are under performance pressure, otherwise zero. *Performance Pressure Historical* sets

[20] We account for each separate coach-team dyad. For example, Zinédine Zidane was appointed head coach of Real Madrid from 01/2016 – 05/2018 and then again from 03/2019 – 06/2021, which enters our analysis as two separate coach-team dyads.

alpha equals 0.75 to calculate the weighted exponential moving average[21] in columns (2) and (5). We further capture a team's preseason expectations relying on *elo ratings* from the website www.clubelo.com. Specifically, we build a league-table rank based on preseason elo ratings and deviations from these expectations are captured by the variable *Performance Pressure Elo* in columns (3) and (6).

Our results are also robust to these alternative specifications of performance pressure situations. Columns (1) – (3) reveal that all interaction coefficients between the performance pressure proxies and *Luck* are negative and significant. Moreover, columns (4) – (6) show that the interaction coefficients between the pressure proxies and bad luck remain positive and significant. However, we still do not find support for the reinforcing role of performance pressure in instances of good luck. Overall, and among all alternative specifications, our conclusion remain qualitatively the same.

Insert Table 4 about here

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5 DISCUSSCION

Consistent with prior research on outcome bias (Brownback & Kuhn, 2019; Gauriot & Page, 2019), we find that principals evaluate agents based on luck. Since we also differentiate between outcome biased evaluations based on bad luck and good luck, our analysis suggests that principals penalize agents for bad luck but do not reward them for good luck.

This finding could be attributed to an asymmetrical response of principals to agents' experience of bad luck compared to good luck. This reasoning receives support from the long-documented

[21] To derive the team's last season historical aspirations level we proceed in two steps. First, we rely on www.transfermarkt.com to receive historical end-season league table rankings. Then we set the last season's HAL at zero the first time we have consecutive observations available. For example, RB Leipzig records the first historical end-season league table rank in 2009/2010. Thus, to calculate the HAL in the 2010/2011 season we calculate 0.75 * $Rank_{t-1}$ + 0.25 * 0. HAL_{t-1}. If, for example, the final rank of a team who was playing in the second-tier league in a given season was five and the second-tier leagues has 20 teams and the first-tier league has 20 teams, a rank of 45 would be assigned for that season. Moreover, the HAL is always equals the highest possible rank in the top five league if a team's HAL would be higher than the highest possible rank. Teams that got promoted last season receive a value of 20 (respectively 18 for the Bundesliga) for the $Rank_{t-1}$ variable.

negativity bias in attentional allocation (Smith et al., 2006), which builds on the reasoning that negative stimuli and positive stimuli are of distinct intensity (Baumeister et al., 2001; Ito et al., 1998; G. Peeters & Czapinski, 1990). Since negative events cause stronger cognitive reactions than neutral or good ones (Ito et al., 1998; Taylor, 1991), agents receive less credit for good outcomes than they receive blame for bad outcomes (Erkal et al., 2022). One potential conclusion from this could be that blame is a primary driver of outcome bias (Gurdal et al., 2013).

However, there is no consensus on this matter in the broader literature. For example, König-Kersting et al. (2021) find that in the context of financial agency principals' outcome-biased evaluations are more pronounced after good outcomes than bad outcomes. Our finding may further appear puzzling in the realm of the broader literature reporting that CEOs are rewarded for luck, which is reflected in their compensation (Bertrand & Mullainathan, 2001). Building upon this, Amore and Schwenen (2022) conclude that conditional on change of employment, lucky CEOs are rewarded with higher pay at new firms. Moreover, prior literature even highlights an asymmetry in pay for luck by emphasizing that CEOs are more rewarded with increased pay for good luck than they are penalized with a pay decrease for bad luck (Garvey & Milbourn, 2006). Recently, however, Daniel et al. (2020) did not find any asymmetry in pay-for-luck, indicating that CEOs are similarly rewarded and punished for good luck.

A possible explanation for these partly conflicting findings in the literature could be that rewards and punishment run through different channels. For instance, our dependent variable, the probability of managerial dismissal, may effectively capture punishment but represents only an imperfect proxy for reward. Likewise, compensation could serve as a suitable measurement for rewards, while capturing punishment only partially. Support for this notion stems from the argumentation that if reward and punishment constitute two distinct categories, they are unlikely the opposite of each other (Fiorillo, 2013). To contribute to this debate in the outcome bias literature, future research may solve this issue by developing a measurement that is able to even more qualitatively proxy punishment and reward on a common scale (Kubanek et al., 2015).

Another explanation for our finding that good luck has no effect on the managerial dismissal probably might be related to a potential shortcoming of our paper. Since our luck measurement only captures a specific aspect of luck, we may overlook other sources of (good) luck. As a result, our luck measurement could potentially represent a slightly better proxy for bad luck than it is for good luck.

Notwithstanding these potential setbacks, the novel and important contribution of our paper to the literature on outcome bias is that neglecting the impact of outcome-induced performance pressure on outcome biased evaluations leads to an underappreciation of outcome bias. This has crucial implications in the realm of the high-stakes evaluation decision of managerial dismissal. Particularly in the wake of performance pressure, a scenario in which subsequent performance improvements are urgently needed, the costs of replacing an unlucky but skilled agent before contract expirations seem substantial. Since only managerial dismissal after actual bad performance increase subsequent performance compared to a control group of non-dismissal with similar bad performance (Flepp & Franck, 2021), urgently needed subsequent performance improvements seem unrealistic if principals replace an unlucky agent under performance pressure. Crucially, doing so may even lead to a decrease in performance compared to when the agent would have stayed in office, which simultaneously further increases performance pressure on principals.

By highlighting the moderating role of performance pressure in outcome biased evaluations, we also raise important questions on potential de-biasing strategies. To develop remedies, the understanding of contextual factors that accentuate or reduce cognitive biases is essential (Soll et al., 2015). A semi-promising strategy involves raising decision-makers' awareness by emphasizing the significance of avoiding important decisions when depleted, distracted (Soll et al., 2015), and thus, when decision-makers face performance pressure. Another, potentially more promising, option could nudge decision-makers to rely on analytical, data-driven approaches (Flepp & Franck, 2021; Soll et al., 2015) to evaluate the informativeness of outcomes, similar to what has been done in *Moneyball* (M. Lewis, 2003). In connection to the latter, our findings might also represent a behavioral opportunity (Denrell et al., 2019) by identifying skilled but unlucky agents to potentially gain a competitive advantage.

6 CONCLUSION

Attempting to emphasize the neglected impact of performance outcomes on the emergence of performance pressure, this paper seeks a nuanced understanding of outcome bias under such performance pressure. Grounded in the argumentation that performance pressure impairs cognitive abilities and increases reliance on heuristics, our hypotheses and findings suggest that outcome-induced performance pressure accentuates the consideration of luck in evaluation decisions. Our empirical results emphasize that this effect is predominantly driven by bad luck. Agents facing bad luck are more likely to be penalized for bad luck when principals experience mounting performance pressure. Overall, our findings support the idea that overlooking the impact of performance outcomes on performance pressure may lead to an underestimation of outcome bias.

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Table 1: Descriptive statistics and pairwise correlations of the main variables of interest

	Mean	Sd	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 Coach Dismissal	0.010	-	0	1	1										
2 Luck	0.176	1.556	-6.500	9.500	-0.022	1									
3 Bad Luck	0.436	0.826	0.000	6.500	0.025	-0.738	1								
4 Good Luck	0.612	1.099	0.000	9.500	-0.013	0.862	-0.294	1							
5 Performance Pressure	-0.626	5.183	-19	17	0.087	-0.070	0.031	-0.076	1						
6 Relegation Pressure	0.117	-	0	1	0.112	-0.017	0.010	-0.016	0.300	1					
7 Win Percentage	0.395	0.214	0.000	1.000	-0.079	0.033	-0.012	0.038	-0.313	-0.458	1				
8 Tenure	723.180	803.279	0	7,894	-0.026	0.010	0.002	0.016	0.060	-0.056	0.042	1			
9 Games played	17.897	10.811	1	38	-0.009	0.025	0.218	0.199	-0.041	-0.052	0.027	0.108	1		
10 Focal Key Injuries	1.562	5.536	-15.000	71.000	0.003	-0.142	0.167	-0.076	0.070	-0.020	-0.010	0.050	0.134	1	
11 UEFA Period Opponent	0.201	-	0	1	0.008	-0.005	0.021	0.008	0.011	0.033	-0.045	-0.003	-0.054	-0.002	1

Notes: Descriptive statistics and pairwise correlations are calculated for 15,458 team observations. We do not report standard deviations for dummy variables.

Table 2: Main Results

	Coach Dismissal (1/0)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Main Effects								
Luck	-0.00141***	-0.00179**	-0.00219**	-0.00124*				
	(0.001)	(0.001)	(0.001)	(0.001)				
Bad Luck					0.00273**	0.00437**	0.00517***	0.00201
					(0.001)	(0.002)	(0.002)	(0.002)
Good Luck					-0.00056	-0.00003	0.00040	-0.00077
					(0.001)	(0.001)	(0.001)	(0.001)
Moderating Effects								
Performance Pressure			0.00418***				0.00351***	
			(0.000)				(0.000)	
Performance Pressure x Luck			-0.00056***					
			(0.000)					
Performance Pressure x Bad Luck							0.00154***	
							(0.000)	
Performance Pressure x Good Luck							0.00017	
							(0.000)	
Relegation Pressure				0.03982***				0.02638***
				(0.006)				(0.007)
Relegation Pressure x Luck				-0.00427				
				(0.004)				
Relegation Pressure x Bad Luck								0.02125***
								(0.008)
Relegation Pressure x Good Luck								0.00655
								(0.005)

Table 2: Main Results (continued)

Controls								
Win Percentage		-0.02985***	0.02909***	-0.01376**		-0.02967***	0.02499***	-0.01657***
		(0.006)	(0.007)	(0.006)		(0.006)	(0.007)	(0.006)
Tenure		0.00009*	0.00011**	0.00009*		0.00009**	0.00012***	0.00009*
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Games Played		0.00004	-0.00003	0.00010		-0.00004	-0.00022	0.00002
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Key Focal Injuries		-0.00004	-0.00010	-0.00010		-0.00007	-0.00008	-0.00011
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
UEFA Period Opponent		0.00137	0.00076	0.00106		0.00120	0.00050	0.00080
		(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
Observations	15,458	15,458	15,458	15,458	15,458	15,458	15,458	15,458
R-squared	0.001	0.073	0.079	0.080	0.001	0.073	0.081	0.082
Team-Season FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Coach FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: OLS regressions with robust standard errors clustered on games in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Cox Proportional Hazard Models

	Coach Dismissal (1/0)					
	(1)	(2)	(3)	(4)	(5)	(6)
Luck	-0.16834***	-0.10699*	-0.13737*			
	(0.060)	(0.063)	(0.074)			
Bad Luck				0.31315***	0.23066**	0.23122*
				(0.095)	(0.111)	(0.119)
Good Luck				-0.00054	0.01967	-0.03401
				(0.089)	(0.090)	(0.113)
Performance Pressure		0.15010***			0.14125***	
		(0.016)			(0.017)	
Performance Pressure x Luck		-0.02255**				
		(0.011)				
Performance Pressure x Bad Luck					0.03147*	
					(0.017)	
Performance Pressure x Good Luck					-0.00751	
					(0.018)	
Relegation Pressure			1.66437***			1.42885***
			(0.209)			(0.249)
Relegation Pressure x Luck			-0.13615			
			(0.126)			
Relegation Pressure x Bad Luck						0.40630**
						(0.171)
Relegation Pressure x Good Luck						0.09315
						(0.149)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Log Pseudolikelihood	-689.361	-643.322	-653.883	-687.354	-641.302	-649.485
Wald x^2	138.14	230.97	240.54	145.8	264.81	286.15

Notes: Cox proportional hazard models with right-censoring based on coach spell durations with robust standard errors clustered on coach-team dyads. Clustering the standard errors on the coach, team, or game level does not alter the results. We report coefficients instead of hazard ratios. The analysis includes 387 potential subjects (coach-team dyads) at risk and 149 failures (dismissals).
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Alternative Operationalization of Performance Pressure

	Coach Dismissal (1/0)					
	(1)	(2)	(3)	(4)	(5)	(6)
Luck	-0.00020	-0.00235**	-0.00220**			
	(0.001)	(0.001)	(0.001)			
Bad Luck				-0.00065	0.00552***	0.00488***
				(0.001)	(0.002)	(0.002)
Good Luck				-0.00061	0.00059	0.00035
				(0.001)	(0.001)	(0.001)
Performance Pressure Dummy	0.01733***			0.01012***		
	(0.003)			(0.003)		
Performance Pressure Dummy x Luck	-0.00414**					
	(0.002)					
Performance Pressure Dummy x Bad Luck				0.01282***		
				(0.004)		
Performance Pressure Dummy x Good Luck				0.00205		
				(0.002)		
Performance Pressure Historical Dummy		0.00419***			0.00341***	
		(0.000)			(0.000)	
Performance Pressure Historical x Luck		-0.00055***				
		(0.000)				
Performance Pressure Historical x Bad Luck					0.00170***	
					(0.000)	
Performance Pressure Historical x Good Luck					0.00028	
					(0.000)	
Performance Pressure Elo			0.00420***			0.00342***
			(0.000)			(0.000)
Performance Pressure Elo x Luck			-0.00057***			
			(0.000)			
Performance Pressure Elo x Bad Luck						0.00173***
						(0.000)
Performance Pressure Elo x Good Luck						0.00020
						(0.000)

Table 4: Alternative Operationalization of Performance Pressure (continued)

Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,458	15,458	15,458	15,458	15,458	15,458
R-squared	0.075	0.079	0.079	0.077	0.081	0.081
Team-Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Coach FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions with robust standard errors clustered on games in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Interaction of bad luck and performance pressure

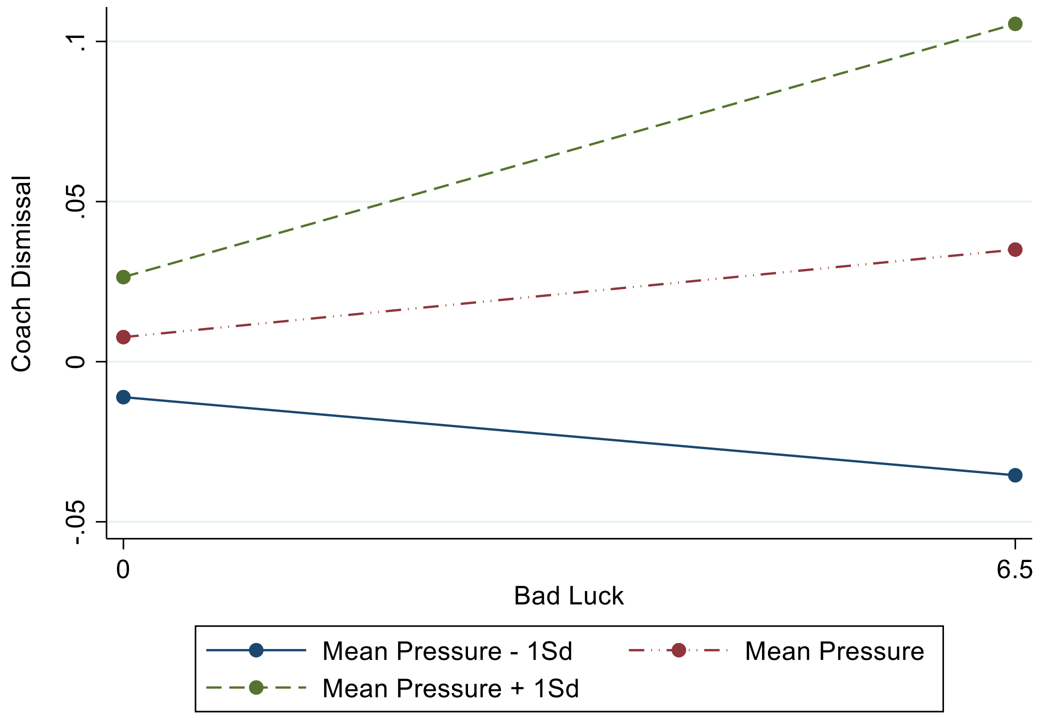
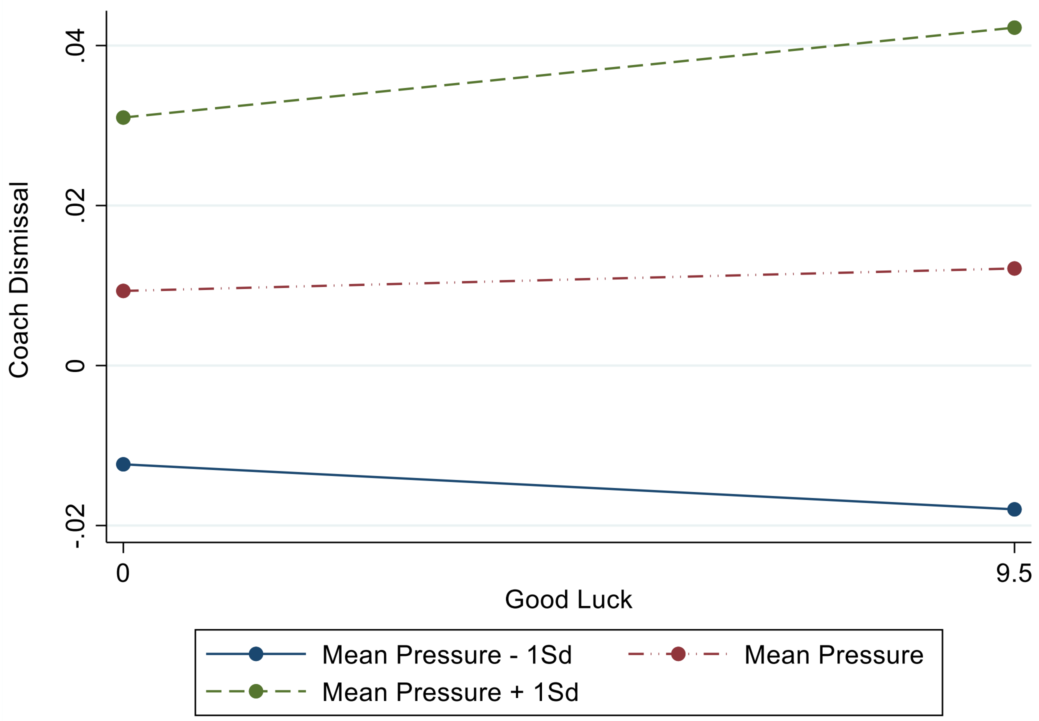


Figure 2: Interaction of good luck and performance pressure



APPENDIX

Table A1: Validity of key opponent injuries and their accumulation as instrument for exogenous luck

	Goal Difference	*Points*	*Rank*	*Rank*
	(1)	(2)	(3)	(4)
Key Opponent Injuries	0.11759***	0.09178***		
	(0.026)	(0.019)		
Luck			-0.10077***	
			(0.019)	
Bad Luck				0.14792***
				(0.033)
Godd Luck				-0.06601**
				(0.027)
Observations	18,058	18,058	18,058	18,058
R-squared	0.149	0.125	0.808	0.808
Team-Season FE	Yes	Yes	Yes	Yes

Notes: OLS regressions with robust standard errors clustered on games in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Real data example as illustration of the construction of the luck, bad luck, and good luck variables

Team	*Season*	*Games played*	*Key opponent injuries*	*Cum. key opponent injuries*	*Median cum. key opponent injuries*	*Luck*	*Bad Luck*	*Good Luck*
Arsenal	18/19	1	0	0	0	0	0	0
Arsenal	18/19	2	0	0	0	0	0	0
Arsenal	18/19	3	0	0	0	0	0	0
Arsenal	18/19	4	0	0	0	0	0	0
Arsenal	18/19	5	1	1	1	0	0	0
Arsenal	18/19	6	1	2	2	0	0	0
Arsenal	18/19	7	0	2	2	0	0	0
Arsenal	18/19	8	0	2	2	0	0	0
Arsenal	18/19	9	0	2	2	0	0	0
Arsenal	18/19	10	0	2	2	0	0	0
Arsenal	18/19	11	0	2	2.5	-0.5	0.5	0
Arsenal								
Arsenal	18/19	16	0	4	5	-1	1	0
Arsenal	18/19	17	1	5	5	0	0	0
Arsenal	18/19	18	0	5	6	-1	1	0
Arsenal	18/19	19	0	5	6.5	-1.5	1.5	0
Arsenal	18/19	20	0	5	6.5	-1.5	1.5	0
…								
Arsenal	18/19	27	0	8	9	-1	1	0
Arsenal	18/19	28	3	11	9	2	0	2
Arsenal	18/19	29	1	12	10.5	1.5	0	1.5
Arsenal	18/19	30	0	12	10.5	1.5	0	1.5
…								
Arsenal	18/19	38	0	17	16	1	0	1

Notes: This is a real data extract that shows the development of luck, bad luck, and good luck for Arsenal among the 2018/19 season.