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The Role of Hierarchical Differentiation for the Effectiveness of Soccer Teams

Sebestyén András Huszár

Freie Universität Berlin

Abstract

The impact of hierarchical differentiation on team effectiveness is heavily discussed in scientific research with strong arguments lined up on both the pro and the contra sides. To contribute to this debate, I investigated the relationship between a specific facet of hierarchical differentiation, pay dispersion, and team effectiveness. I collected data from five seasons of Premier League and conducted a regression analysis to study the effect of pay dispersion on team performance, cooperation and aggressivity. The empirical results show that pay dispersion is positively and directly associated with aggressivity, whilst its relation with team performance and cooperation is moderated through the financial might of teams. The significant interaction effect for team performance means that pay dispersion has a significant negative effect for high financial might teams, and a weak positive effect for low financial might teams. For cooperation the interaction shows a significant positive effect for the low financial might teams and a weak negative effect for the high financial might teams. Thus, I conclude that pay dispersion indeed affects team effectiveness, however the economic power standing behind the teams needs to be considered.

Keywords: hierarchical differentiation; pay dispersion; Premier League; sports data; team performance

1. Introduction

After taking the reins of Manchester City in 2016 Pep Guardiola said "what we want is so simple: when the opponent has the ball, take it back as quick as possible. When we have the ball, try to move as quick as possible, to create as much chances as possible. That's all. And good team spirit." (Manchester City, 2022). In many ways he epitomized the quintessence of team success. Effectiveness and efficiency in reacting to the ever changing currents of the environment and creating chances of success, through cooperation and coordination, all the while retaining the internal harmony of the team. The simple, or leastwise simple to understand, ends however scarcely imply equally simple means. Neither in soccer, nor in management.

One hotly debated factor greatly impacting team success is the presence of hierarchical structures, and even more so of hierarchical differentiation. A predominant manifestation of hierarchical differentiation is the dispersion of pay, which, for better or worse, has the capacity to greatly disrupt existent hierarchical structures. In the 2021/22 season of Premier League, Cristiano Ronaldo joined his old club Manchester United with a salary that exceeded the salary of the second highest paid player (David De Gea) by 37%. That season Manchester United ranked the lowest it has in the last five seasons, 6^{th} place, and it was the only season among the last five they failed to collect at least 60 points. Similarly, in the 2020/21 season Gareth Bale rejoined Tottenham with a salary exceeding that of the second highest paid players (Harry Kane and Tanguy Ndombele) by 200%, and the season ended with Tottenham being unable to crack the top 6 of Premier League, the only time they failed to do so in the last five seasons. The question arises, are these isolated cases of misfortune, or is there a deeper connection between pay dispersion and team success.

Literature indeed exists investigating the effects of pay dispersion on team effectiveness, yet there are competing theories and findings, with the debate reaching consens seeming quite improbable. Lazear and Rosen (1981) argued

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that increased pay dispersion will enhance group performance, through motivating increased competition and individual performance. On the contrary, other theories claim pay dispersion to have an adverse effect on group effectiveness, due to increased disconcert and disrupted cohesiveness (Akerlof & Yellen, 1990; Ramaswamy & Rowthorn, 1991). Examining sports teams, quite suitable to this stream of research due to the apparent ease of quantifying performance, Depken and Lureman (2018) found support for pay dispersion hampering team performance, whereas Torgler and Schmidt (2007) discovered both improving and hindering effects.

What is apparent, that both in the theoretical and in the empirical realm there is much controversy around the impact of hierarchical differentiation and pay dispersion on team effectiveness. And indeed, that is the aim of my present thesis, to contribute to this ongoing debate. My fundamental research question is, how does pay dispersion relate to team effectiveness. Strongest focus is laid upon pay dispersion's influence on the performance of the team, however I strive to shed light on pay dispersion's impact on cooperation and aggressivity as well. To that end I will be analyzing Premier League teams. Furthermore, as both in business organizations and in soccer teams, the financial might standing behind a team is a force of doubtless magnitude, I seek to uncover the interplay between financial might and pay dispersion, i. e. their possible interaction in shaping team effectiveness.

My thesis contributes to research by showing the significant moderating effect of financial might, which alters the influence of pay dispersion on team performance. I found evidence that pay dispersion has opposing effects on the performance of the high and low financial might teams. Pay dispersion negatively impacted the performance of high financial might teams, whereas it appeared to lightly increase it for the low financial might teams. Findings showed similarity for cooperation, yet this time the increasing effect for the low financial might teams being significantly positive, and the decreasing for high financial might teams appearing lightly negative. For aggressivity there was no interaction, yet pay dispersion itself did increase aggressive behavior. The explanation for the contrary effects caused by the interaction might lie in the different challenges teams face and the different perceptions players have of themselves and their teams. The discovery of this interaction effect furthers the understanding of how pay dispersion impacts team effectiveness.

The structure of the thesis is as follows. The next chapter offers a brief overview of relevant literature and offers insight in the usage of sports data in managerial research. The third chapter introduces the dataset and describes the regression analysis. In the fourth chapter the results of my hypothesis testing are presented, moreover the second half of the chapter contains a supplemental analysis, testing for interaction effects and the corresponding results. The last chapter reveals a discussion of the findings, detailing the theoretical implications of my thesis.

2. Theoretical background

As previously phrased in the research question, my research revolves in essence around investigating the impact of a certain type of hierarchical differentiation on the effectiveness of teams. Therefore, in this unfolding section I will delve deeper in the core concepts studied, and also offer a brief overview of the most relevant research papers assessing kin phenomena. Moreover, in this chapter I aim to derive my three hypotheses, that will serve as the foundations of my analysis. At last, I will argue for the noteworthy benefits of relying on sports data in researching business organizational and managerial phenomena.

Hierarchy is a concept as ancient as human history. Born out of what once had been a necessity for survival, it had shaped human societies for ages, and as its very construct is inherently and unswervingly human, it will continue to do so. Be it big-game hunting in the age of spear and bow, or the establishment of strategic alliances to reap the competitive benefits of interorganizational networking, for the ultimate success of human groups coordination and cooperation are of utmost importance (Halevy et al., 2011, p. 33). There ever was a need for structure that puts constraints on the adverse aspects of human nature, and at the same time enables virtues to strive and yield benefits (Halevy et al., 2011). Notwithstanding the doubtless existent possibilities (and examples) of failure, this indeed is a crucial facet of what hierarchy is meant to provide.

Magee and Galinsky define hierarchy as "an implicit or explicit rank order of individuals or groups with respect to a valued social dimension" (2008, p. 354). This definition highlights that the degree of awareness might vary greatly between individuals or groups. Some may not perceive that they are part of the hierarchy, but that does not change their embeddedness. Moreover, it emphasizes that there may exist a vast array of aspects by which hierarchy is determined ("valued social dimension"). There is no singular prime measure of hierarchy, although some dimensions do gain more importance over others in given situations. It is a process of social adoption, where certain dimensions might be selected to form the basis of formal hierarchies, or where certain dimensions might organically emerge as commonly valued and birth informal hierarchies. These processes resulting in the creation of hierarchical forms of social relationships constitute the phenomenon called *hierarchical differentiation* by Magee and Galinsky (2008, p. 354).

Groups and teams do form integral parts of any given organization. They are essential to functioning and they produce outcomes, therefore the desire to enhance their effectiveness is a natural implication of striving for the good of an organization. Moreover, for organizations embedded in any competitive environment, the analysis and improvement of the results produced by teams is essential for survival. The appeal of increasing team effectiveness is thus trivial, yet the means are not quite so. The definition of team effectiveness is neither straightforward, nor unitary. Dimas et al. (2023, p. 3) argue that to measure team effectiveness there cannot be one unanimously accepted criterion found, as team effectiveness inherently has different meanings and implications for different stakeholders (2023, p. 3). For instance, the manager in charge of a work group might have vastly different understanding of team effectiveness as opposed to the employee working in the group or the customer for whom the group is producing. Dimas et al. confirm this assumption by reviewing team effectiveness literature. Team effectiveness is a multidimensional construct of different facets (2023, p. 3).

An approach oftentimes employed in order to assess the economical dimension of team effectiveness is measuring team performance. A definition offered by Devine and Philips (2001, p. 512) explains team performance as “the degree to which a team accomplished its goal or mission”. Although not always trivial, possibly a criteria should be chosen that best captures the overall achievements a team has made to accomplish its mission. In my thesis this facet of team effectiveness, team performance, stands in major focus and I aim to find an objective and quantifiable way to measure it.

The literature examining the relationship between hierarchical differentiation and team effectiveness dates back long ago. In 1968 Bridges et al. published a study examining the effects of hierarchical differentiation on the efficiency and productivity of teams, as well as on their risk-taking behavior. They found that hierarchical differentiation had adverse effects on the productivity and efficiency of groups, with the hierarchically undifferentiated groups triumphing in both regards. Moreover, it was showed that hierarchy also hampers risk-taking behavior. It needs to be mentioned however, that Bridges et al. examined groups of quite small size (merely four subjects pro group), and the research revolved mainly around problem solving and idea generation.

Quite contrarily Halevy et al. (2011) theorize a multilayered positive relationship between hierarchical differentiation and organizational success. They argue that hierarchy supports coordination and voluntary cooperation, whilst reducing conflicts. Moreover, that hierarchy incentivizes performance and thus increases motivation, and also constructs a psychologically rewarding environment. Albeit, concluding that the presence of hierarchical differentiation is overwhelmingly beneficial for the performance of an organization, they do identify certain moderating factors. Such as degree of task interdependence, which the higher, the more need it constitutes for hierarchy (for comparison, see the juxtaposition of basketball and baseball in Keidel (1987)), legitimacy of the hierarchical rank order, and the (mis)alignment of bases of hierarchy (as power, status, prestige, etc.)

Ronay et al. (2012) also investigated the effects of hierarchical differentiation on group productivity. The experiments they conducted showed that indeed, as Halevy et al. (2011) theorized, groups with considerable hierarchical differentiation outperformed undifferentiated groups when it came to tasks of high procedural interdependency. And at the same time they found no effect of hierarchical differentiation on tasks procedurally independent. Ronay et al. noted that their research focused mainly on hierarchical differentiation founded in differences of power and dominance, and other bases of hierarchy might be worthwhile to examine as well.

Kampkötter and Sliwka investigated the question in their paper (2018), whether supervisors should differentiate more between employees based on their performance, in the process of performance evaluation and bonus allocation. Their findings show that the willingness to differentiate between employees does have a positive effect on their performance, and consequently on the rise of future performance bonuses (individually and at large). However, notably this effect is stronger at the higher hierarchical echelons, whilst reversing to some degree at the lowest of levels. Therefore the authors suggest firms should employ stronger differentiation at the middle and higher levels, whereas being cautious of utilizing it at the bottom. Nevertheless, it seems, that much like with groups, hierarchical differentiation does have a complex and somewhat blurry effect on individuals, moderated by a variety of factors.

To tackle some of the highly difficult questions surrounding the inconsistent findings about the relationship of hierarchy and performance, Hays et al. (2022) offer a nuanced approach to study the impact of hierarchical differentiation on team performance, where they distinguish between two distinct types of differentiation, based on power and status. Hays et al. argue that the two hierarchies might interplay and co-effect team outcomes. They provide evidence that status differences beget a more competitive and less cooperative climate (p. 2098). Furthermore, they identify this as the determinant factor as in when power differences have detrimental effects on team performance (when both power and status differentiating is high).

In another recent paper To et al. (2022) propose a novel extension to models describing the relationship between hierarchy and performance. Their research understands team performance as not merely the result of hierarchy, but also as one of its future determinants. This is an idea quite similar to, although never explicitly stated in the paper to be derived from, the duality of structure, a core theorem of the highly influential structuration theory of Anthony Giddens (1984). As Giddens explains, structure enables agency, providing room for agents to act, and at the very same time structure is reproduced through agency and the action and interaction of agents. It is not a dualism where only one or the other exists, but a duality where one cannot exist without the other. What To et al. describe is kin to this perspective. They argue that hierarchical differentiation breeds performance success, and performance success reinforces or reshapes the hierarchical structure. Furthermore, they suggest the presence of an attribution process, as in a team greater influence is granted to members who are believed to be the causes of success.

As findings of research studies regarding the relationship of team effectiveness and hierarchical differentiation in particular, and hierarchy in general, were largely mixed, at best disaligned, at worst contradictory, Greer et al. (2018) commenced with an overarching meta-analysis review of this scientific landscape (evaluating 54 papers). They identified two competing perspectives among scholars investigating hierarchy, the “functionalist perspective” and the “conflict perspective”. The perspective labeled as functionalist is a generally positive view on hierarchy, claiming hierarchy to enhance team effectiveness via improved coordination and cooperation processes. Whereas the conflict perspective offers a much harsher view on hierarchy, mainly highlighting its adverse effects on team effectiveness due to the amplification of a more conflict-laden environment. Greer et al. note that there has been a multitude of contingency factors identified in order to solve the discrepancy and explain the conflicting research results, such as task characteristics, team structure or form of hierarchy. Nevertheless, their results did not support the functionalist perspective on hierarchy (thus the existence of its significant improving effects on team effectiveness) in general. However, their research strongly supported the dysfunctional views on hierarchy, and showed that hierarchy negatively impacts team effectiveness, largely due to increasing “conflict-enabling states.”

As mentioned above, the particular facet of team effectiveness that I strive to examine in my present thesis is team performance. And much like with the concept of team effectiveness, there are multiple aspects of the concepts hierarchy and hierarchical differentiation as well. In my research I am investigating soccer teams. In soccer teams formal hierarchy is not particularly prevalent or established, aside from the distinctive role of team captain, the chosen on-pitch leader of a team. Therefore, what I aim to examine is the informal hierarchy, and the impact of hierarchical differentiation resulting from this informal hierarchy.

Like previously explained, considering the definition of Magee and Galinsky (2008), there might be a variety of determinants of informal hierarchy present in any group of individuals. In my research sample, soccer teams, the seniority of a player in the team or the league, or the age of a player (which two, seniority and age, does not necessarily coincide), their current form in the season or their salaries, all may contribute to the shaping of the social rank order, known as hierarchy. The aspect of hierarchical differentiation I have chosen to understand and investigate within soccer teams was the differences in salaries, i. e. *pay dispersion*. This is an apt metric to symbolize hierarchical differences, as salaries are due to their very nature quantified, and not purely quantified, but in a form easy to grasp and perceive for all team members, or the average observers. Moreover, higher salaries are undoubtedly more desirable, and they do provide considerable incentives for soccer players. Higher salaries also show that a certain player is more valued, and more valuable to the club than other players are. Thus pay dispersion provides a within-team social rank order, one easy to discern, and one wherein every player of a team may be placed. To model pay dispersion I will use, in line with literature (Harrison & Klein, 2007), the metrics Gini index and the coefficient of variation (see more *Independent variables*).

Thus to redefine the research topic of my thesis (the relationship between hierarchical differentiation and team effectiveness) more accurately, I aim to shed light on the relationship between pay dispersion and team performance. Drawing on Greer et al.’s meta-analytic literature review (2018) and Hays et al.’s more recent study (2022) I surmise that pay dispersion causes detrimental fractures in a team’s internal integrity, due to working as a causal agent for creating and escalating more conflicts, and therefore has an overall adverse impact on team performance. Consequently, I formulate my first hypothesis (H1) to test this effect as follows:

> **Hypothesis 1.** *Pay dispersion is negatively related to the performance of teams, as in higher pay dispersion resulting in lesser team success.*

When examining the functionalist perspective that claims hierarchy improves the cooperation and coordination processes of teams, Greer et al. (2018) found no significant support for this notion in their meta-analysis. Furthermore, Hays et al. (2022, p. 2098) found evidence that hierarchical differentiation does make a team’s climate more competitive and less cooperative. Therefore I theorize that hierarchical differentiation diminishes cooperation, meaning that pay dispersion may adversely affect the cooperative behavior of teams. The duty of hypothesis two (H2) is to test this particular effect.

> **Hypothesis 2.** *Pay dispersion is negatively related to the cooperative behavior of teams, as in higher pay dispersion resulting in less cooperation within the team.*

The assumptions preceding the first two hypotheses suggest that hierarchical differentiation (in this thesis pay dispersion in particular) raises the level of competitiveness within a team (H2) and creates room for conflicts between individuals of the team (H1). Hierarchical differentiation thus is warranted to cause enhanced tensions within groups, and quite reasonably arises the question whether hierarchical differentiation can in fact result in explicit misbehavior. In a study examining interpersonal competitiveness Dumblekar (2010) found a close relation between competitiveness and aggressivity. Yet, research regarding this connection is not particularly exhaustive. Albeit, studies can be found in somewhat differing fields, as Schmierbach’s paper from 2010, which examined the link between competitiveness and aggression in online gaming, or the paper of Krisnadewi and Soewarno (2020) wherein competitiveness was determined as a major factor in causing more aggressive organizational behavior. The line of argumentation is quite similar nevertheless in all the aforementioned cases. Competitition increases pressure, with pressure increasing frustration and evoking the need to perform better, which results in aggressive behavior. Now, given the hypothesized increased within-team competitiveness and the creation of a more conflict-laden environment I suspect the presence of a relationship between hierarchical differentiation and aggressivity. The difference in salaries doubtless creates tension within the soccer teams, as it makes it most easy to compare and understand the rank order, by making it quite evident which players are valued more by the club. Moreover, it is an apparent monetary benefit and thus a stark difference between teammates who, with a slight oversimplification, do have the same jobs. And this indeed I aim to test in my data analysis, therefore the third hypothesis of my research reads as follows.

Hypothesis 3. *Pay dispersion is positively related to aggressivity, with higher pay dispersion enhancing aggressive behavior of the team.*

As stated above, to examine my research question and to test the three derived hypotheses I will utilize sports data. Now, the questions may arise, why use sports data to study business organizational phenomena, what benefits does it bring and what constraints does it mean for the research.

The usage of data collected from professional sports in management research is not a new-found approach. In 1984 Robert Keidel had already published an article (and the beginnings of using sports data in management research date even further back, see e. g. Gamson and Scotch (1964)), where he argued for the applicability of sports data in organizational setting, and determined the structure and management of the three major professional sports (in the US, baseball, basketball and football, providing models for vastly different team structures) as useful for understanding and shaping business organizations, or as he phrased for "determining their best game plans" (1984, p. 5). What Keidel showed in his article were the striking similarities between sports teams performing on the pitch and organizational groups, and between sports teams and organizations as a whole. Among the many parallels, and reasons why sports teams are apt models for businesses, Keidel listed the "need to compete externally" alongside with the "need to cooperate internally", furthermore the necessity of strategic human resource management and the fact that sports teams do resemble generic structures (1984, p. 12). These structures aid managers in understanding how their organizations work.

In his 1987 work Keidel expanded his triadic sports-model framework integrating it with several core constructs of organizational literature. The three major US professional sports serve as metaphors for autonomy of organizational parts and independence (baseball), hierarchical control and dependence (football) and voluntary cooperation and interdependence (basketball, interchangeable with soccer according to Keidel) (1987, p. 592 and 596). Moreover, Keidel argues that sports data has further benefits, such as the easy accessibility of high quantities of high quality objective data and unified measures that unambiguously quantify performance and success (1987, p. 608).

In their article from 2012, Day et al. reviewed studies that combined sports science and the field of organizational behavior, to assess the core themes and contributions of such endeavors. Their findings reinforce that professional sports can be used excellently to model the fundamental issues between competition ("getting ahead") and cooperation ("getting along"), moreover also to study succession, performance and motivation and dealing with pressure. They argue that sports are ever so suited to be analyzed as they offer a "living laboratory" where "life simplified" may be observed. The rules are explicit and known to all players and agents, moreover there are clear boundaries constraining the action, and winners and losers may be unanimously identified (2012, p. 399). Furthermore, in professional sports large stakes are dependent upon individual and group performance, and as much as entertainment, it is the constant generating of high revenues that stands in cardinal focus. The need to attain high, or leastwise sufficient, financial performance is another factor showing considerable parallel between sports teams and business organizations.

As of writing this thesis, the most recently published review of studies using sports data in management context is the work of Fonti et al. (2023), a literature review of great magnitude, where they identified and assessed 249 papers from the last five decades. Fonti et al. list a multitude of research areas in the field of management, where sports data was utilized to great success in the past years. Such areas include literature around the resource based view, status and reputation, risk-taking behavior, leadership, motivation and many more. The genuine impact of sports data on management research is thus quite apparent in this retrospective view. Furthermore, Fonti et al. highlighted how sports data may advance management research, as in aiding theory building and theory testing, radical theorizing (i. e. moving away from the traditional settings, and thus lessening the binding influence of "taken-for-granted" theoretical perspectives and creating room for novel views (p. 336)), and exploring emerging phenomena (due to high visibility of actors). The authors argue that beyond that sports data could even help alleviating certain concerns regarding management research, as in increasing validity through offering methods for triangulation or providing opportunities to replicate findings of management studies in different and data rich contexts.

However, as Fonti et al. pointed out there do exist certain drawbacks of relying on sports data (2023, pp. 346-348). Accessibility of sports data might diminish to some extent in the future, as organizations who compile and collect high quality datasets are growing increasingly aware of the value of such datasets and will protect them. A deeper understanding of the sporting context is a necessary precondition for analysing such data, which may not be the case for all researchers. For testing certain theories some sport settings might fit only to a limited extent, or simply not at all. Moreover, the researchers need to be aware of the possibilities of path dependencies, which might greatly influence the investigated phenomena, but which are lost once the analysis is transitioned into the realm of sports. And maybe most importantly the question of generalizability. Researchers have to be mindful how, and to what extent, the findings may be extended to business organizational settings, and reflect on the boundaries of sports data when understanding managerial phenomena.

However, the benefits duly outweigh the drawbacks of using sports data, (and Fonti et al. even offer remedies and mitigation approaches). As the last part of my theoretical research I examined the literature that relied on sports data, whilst studying pay dispersion and its effects.

Halevy et al. (2012) investigated the effects of hierarchical differentiation on the sporting success of NBA teams (basketball). The authors defined hierarchical differentiation as the dispersion of pay and of participation in games. They found that hierarchical differentiation increased team performance, due to increased cooperation and coordination. These findings stand in stark contrast to papers predicting hierarchical differentiation to have malign effects on team success, such as Greer et al. (2018) or Hays et al. (2022), and it is contradictory to my predicted H1. Given that according to Keidel (1987) basketball and soccer teams are interchangeable for examining managerial phenomena, this is an interesting premise.

To contribute to research surrounding human resource values and pay allocation Hill et al. (2017) examined teams from the MLB (baseball). They theorized that there is a congruence between the dispersion of human resource values and pay dispersion, moreover that this congruence is positively related to team performance. They found support for their theory, and in addition showed, that this congruence between value and pay dispersion positively moderates the relation between overall resource value and team performance. Whilst these results are doubtless interesting, it has to be noted that, as referred above by the drawbacks listed in Fonti et al. (2023) the characteristics of the scrutinized sport have to be taken into account. As heavily emphasized in Keidel's works (1984, 1987) baseball is a somewhat peculiar sport, where task independency is exceptionally high, and a sport where within team cooperation is not as essential as in other sports (e. g. football or basketball). Therefore to which organizational settings these results may be transferred to have to be carefully chosen.

Mondello and Maxcy (2009) evaluated the impact of pay dispersion and pay incentives on team performance in NFL (football) teams. Contrary to the findings of Halevy et al. (2012) and Hill et al. (2017) and in line with the dysfunctional view of hierarchical differentiation, the authors found a strong negative relationship between pay dispersion and on-field team performance, as in when pay dispersion increases, team performance significantly decreases. An interesting finding of the study was that pay dispersion however did positively correlate with team revenue earned. This is a somewhat paradoxical conclusion, as winning (negatively related to pay dispersion) and team revenue (positively related to pay dispersion) also correlate positively among themselves.

Franck and Nüesch (2011) analyzed the impact of pay dispersion on team performance in professional soccer teams (Bundesliga) and hypothesized the presence of a nonlinear effect. The authors found evidence for a U-formed relationship between pay dispersion and team performance, with moderate pay dispersion being the most detrimental for sporting success and very low levels of pay dispersion and high levels of pay dispersion enhancing team performance. Thus according to Franck and Nüesch teams should either follow an approach revolving around strong individualism or foster a "culture of cooperation" (2011, p. 3047). They also showed that the structure of salaries does effect a team's playing style, with greater pay dispersion increasing offensive and individualistic initiatives, which may be viewed in essence as increased risk-taking behavior.

Also in the realm of soccer did Bucciol et al. (2014) conduct their research, where they investigated the relationship between the performance of Serie A teams and their pay dispersion. A novel contribution of their study was the approach to analyze this relationship whilst employing different definitions of what constitutes a team. Bucciol et al. found, that if taken the narrowest definition of team (i. e. the players who play in a given game), then pay dispersion has a significant negative effect on team performance. In their research this effect of pay dispersion disappeared once they used the wider definition of team, taking into account not only those who directly contributed to the outcome. An interesting and somewhat unexpected finding of their research was moreover, that the detrimental impact caused by high pay dispersion could be attributed to worsening individual performances, but not to decreasing cooperation within the team. This stands partially against the traditional dysfunctional view on hierarchical differentiation, as that assigns the burdened cooperation as one of its pivotal arguments against the benefits of hierarchy.

In a more recent study Di Domizio et al. (2022) examined pay dispersion and team performance, also studying teams of Serie A, the top Italian professional soccer league. They employed weighted wages, meaning that they adjusted salaries with the ratio between the average salary of a given team and the league average. Di Domizio et al. confirmed the significant positive effect of relative wages on team performance, supporting the widespread notion that financially mightier teams do perform better. Moreover their results show a significant negative impact of pay dispersion on team performance. These results contradict to some extent the results of the study of Bucciol et al. (2014), which did not show a significant negative relation between pay dispersion and team performance once looking at the entire roster (only for players involved in the outcome). Albeit both papers studied the Serie A, Bucciol et al. took the results of single matches to measure team performance, whereas Di Domizio et al. focused on the ultimate outcome of the entire season. The discrepancy may lie in the approach Di Domizio et al. took to measure weighted wages, where they attempted to control for the financial power of teams, but at the same time Bucciol et al. also used average pay in their models as a control variable for a very similar end.

Thus there is evidence for both positive and negative effects of pay dispersion on team effectiveness once investigating sports data. Yet, arguments and findings on the side showing a negative impact appear to duly outweigh those standing for a positive. In this thesis I aim to replicate these findings conducting an analysis using data collected from professional soccer, whilst relying on a different setting. In my analysis I will be examining teams in the Premier League, the most high profile soccer league around the world. To my best knowledge, and as of writing this thesis, no study was published that did so. Furthermore, in order to control for the financial power standing behind the teams I take a notably different approach in this thesis (see *Control Variables*, financial_might), compared to what the previously referred studies did.

3. Methodology

3.1. Data collection and model

In the following section of the thesis the research design is introduced, detailing the empirical approach for data collection and analysis. As I have argued above, for its various and numerous advantages, I employed data collected from a professional sport. The chosen sport was soccer and I collected the dataset from the Premier League.

The Premier League is the upperest echelon of the English soccer league system. It was chosen to be the center of my analysis as it is historically understood as one of the most competitive professional soccer leagues (Ramchandani, 2012), and as of writing this thesis it is by large the most valuable soccer league. According to the widely accepted, and in the realm of scientific sports research oftentimes relied on website *www.transfermarkt.de* (Franck & Nüesch, 2011), the entire Premier League constitutes an overall market value exceeding 10.42 billion euros. In comparison, the second most valuable league, LaLiga, the highest Spanish soccer league, is estimated to have an overall market value of merely 4.78 billion euros, less than half of what Premier League is valued (Transfermarkt, 2023). In every season there are 20 teams competing in the Premier League and every team plays against every other competitor twice, thus a team plays altogether 38 games in any given season. A team may win, draw or lose a game, earning three, one or zero points, respectively. At the end of the season three teams are relegated to the Championship, the second highest English soccer league, and in return three teams are promoted to the Premier League. The aim of all teams ever is to collect as many points as possible, avoid relegation and strive for the top of the table to attain the prestigious and very lucrative qualification for the UEFA Champions League.

The final dataset contains seasonal level data of teams, therefore the unit of analysis is a given team's given season. I collected the data from the last five seasons of the Premier League that were completed at the time of writing this thesis, beginning with the 2017/18 season and ending with the 2021/22 season. Consequently, there are in total 100 team-season observations. A variety of metrics (e. g. number of points attained, number of passes completed, number of fouls committed or history, measured in seasons played in the Premier League) was collected using the official website of Premier League, *www.premierleague.com*. Individual-level statistics of players from every season were collected as well, utilizing the aforementioned *www.transfermarkt.de* (e. g. Premier League experience or age, and even tenure of coaches). For payroll data I have used the website *www.spotrac.com*. The individual-level data contributed to computing team-level metrics, such as the average of age, the average of Premier League experience or the variables measuring pay dispersion (see below, *Independent Variables*). The financial data of clubs is made publicly available through *www.gov.uk*, an official public sector information website of the United Kingdom, where an extensive record of all companies' filing history can be found (see more, *Control Variables*, financial_might). The validity of data collected from *www.gov.uk* and from the official website of Premier League is naturally exceptionally high. As I have mentioned above, *www.transfermarkt.de* is indeed a website frequently employed over a lengthy period of time in scientific research, and a website considered reliable (Franck & Nüesch, 2008; Frick, 2011; Lepschy et al., 2020; Torgler & Schmidt, 2007). The website *Spotrac* is also utilized in scientific research for player compensation and contract information (Mills & Winfree, 2018; Soebbing et al., 2022). Therefore concerns regarding the validity and reliability of the data are deemed to be unfounded.

In order to test the hypotheses and investigate the impact of pay dispersion on team performance, cooperation and aggressivity, I estimated several linear regression models. The simple structure of these models was the following (see Equation 1). Explanation for the individual variables follows in detail. I discuss the necessary assumptions for OLS (ordinary least squares) regression at the end of this section of my thesis.

The equation of linear regression models used:

$$Y = \beta_0 + \beta_1 * \text{pay dispersion} + \beta_i * \text{control variables} + \varepsilon \quad (1)$$

where,

- Y = dependent variable (team performance, cooperation or aggressivity)
- β_0 = the intercept
- β_1 = coefficient associated with the measure of pay dispersion, here the Gini index or the coefficient of variation
- pay dispersion = independent variable, Gini index or coefficient of variation
- β_i = coefficients of the control variables
- control variables = history, financial might, average age, average experience, average pay, roster size, coach tenure and past performance
- ε = error term

3.2. Variables

3.2.1. Dependent variables

To measure a team's seasonal performance I used the variable team_performance, which is in essence the number of points collected throughout the given season. This is an apt metric for the purpose, as collecting as many points as possible is what ultimately decides the final league placement of the teams (and higher league placement is an unequivocally positive and desired outcome). The more games a team wins (or does not lose, as draws do bring points), the more points it may collect. 20 teams competed in all the five seasons I have observed (and as a matter of fact ever since the 1994/95 season it always has been 20), and each team in each season did indeed play all of its 38 games. Thus I used the absolute number of points achieved for the variable without any transformation (e. g. using the percentage of maximum points achieved). The maximum number of points theoretically achievable was 114 in all five seasons.

In soccer the most frequent element of play that signifies cooperation and interaction between players of a team is passing the ball. Therefore, as in Franck and Nüesch (2011, p. 3046), to judge the display of cooperativeness within teams I applied the total number of passes a team had completed in a given season as proxy. This second dependent variable I named cooperation.

Several options presented themselves to account for the variable measuring the overall aggressivity of a team, such as the number of yellow cards, red cards or fouls. Albeit red cards undoubtedly signify the most severe and impactful violations of the game and its rules, the idea of relying on them was quickly discarded, as they are far too rare and far too impactful (a red card inevitably means a team losing a player, which in nigh all cases is a most grave setback). A multitude of fouls is awarded with yellow cards, yet the correlation between the number of yellow cards and the number of fouls in the dataset proved to be quite low, 0.317. There may be multiple reasons behind this low correlation. From one side a large portion of fouls is punished with a free kick for the opponent. These may very well be aggressive or hostile actions, yet not necessarily the like of which that results in the player being officially cautioned by the referee (receiving a yellow card). Whereas from the other side there are indeed cases of misconduct punished with yellow cards, that do not coincide with openly aggressive behavior, as delaying the restart of the game or removing the shirt in celebration. Therefore, I chose the number of fouls committed throughout the season by a given team to be the proxy for aggressivity, as it represents the aggressive tone of a team more suitably. This third dependent variable I called aggressivity_f.

3.2.2. Independent variables

The independent variable of this research is the one measuring pay dispersion within a team. This type of within-unit diversity may be categorized as disparity according to Harrison and Klein (2007, p. 1200), and in line with their recommendations I computed the Gini index and the coefficient of variation in order to model pay dispersion (p. 1210). Every single test I performed and every single model I estimated, I repeated with both coefficients in order to check for robustness of my findings. For clarity, only the numbers retained from the calculations with the Gini index are reported in my thesis. The calculated variables for the Gini index and the coefficient of variation show a remarkably high correlation between themselves, with a value slightly exceeding 0.960.

Normally, the Gini index is calculated from dividing the mean of the differences between all possible pairings of units with the size of the mean. However, in case all units are of the same size and they are ordered according to size, then the following Equation 2 yields the Gini index (Damgaard & Weiner, 2000):

$$G = \frac{1}{n}\left(n+1-2\left(\frac{\sum_{i=1}^{n}(n+1-i)\,x_i}{\sum_{i=1}^{n}x_i}\right)\right) \tag{2}$$

where,

- n = roster size, the number of players within a team
- i = index of the population, goes from 1 to n, the order is nondecreasing, with $x_i \leq x_{i+1}$
- x_i = the salary of i player

Still, Biemann and Kearney (2010, p. 591) have shown that the Gini index, as most estimators of diversity, does entail a certain bias. According to the authors, this systematic bias of the Gini index is most burdensome for smaller groups, where the level of disparity is underestimated (p. 591). They suggest using a corrected formula of the Gini index, see Equation 3. As the size of population in my present research corresponds the size of soccer teams, this bias-corrected version of the Gini index is indeed employed to avoid distortion caused by small population sizes.

Bias-corrected formula of Gini index:

$$G_n = G * \frac{n}{n-1} \tag{3}$$

where,

- G = Gini index calculated with the formula of Equation 2
- n = the size of population, here the roster size, the number of players within a team

This bias-corrected version of the Gini index calculated with Equation 2 and 3 is the independent variable, called pay_dispersion_gini.

The index I used to compute the second pay dispersion variable, for robustness tests, was the coefficient of variation (CoV). By definition the coefficient of variation is calculated by dividing the standard deviation with the mean (Bedeian & Mossholder, 2000, p. 286). The formula is present in Equation 4.

Coefficient of variation:

$$CoV = \frac{SD}{\overline{x}} = \frac{\sqrt{\frac{1}{n} * \sum_{i=1}^{n}(x_i-\overline{x})^2}}{\overline{x}} \tag{4}$$

where,

- SD = the standard deviation of player salaries
- $\overline{x}$ = the mean of player salaries
- n = roster size, the number of players within a team
- x_i = the salary of i player

Once again however, Biemann and Kearney (2010, p. 592) advises caution, as they argue the coefficient of variation is inherently biased as well, and once again, more significantly for smaller groups. Given that the standard deviation, which is used to calculate the coefficient of variation, is a biased measure itself, this is unsurprising. The authors recommend using the bias-corrected formula of standard deviation as basis for calculating the coefficient of variation, and show in their paper that this correction indeed yields significant improvement. In order to attain an unbiased estimation of the standard deviation the following formula shall be calculated (p. 589):

$$SD_n = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{q}} \tag{5}$$

This estimation noticeably uses a q value instead of the n, the group size. This q is the denominator of the unbiased estimate of the standard deviation, and is derived from Cureton's value table (1968) to any given group size. Consequently, the bias-corrected version of the coefficient of variation is the ratio of SD_n and the mean. This is the second version of the independent variable, and I named it pay_dispersion_cov.

3.2.3. Control variables

Following the praxis of scientific sports research I included a number of control variables in my model. These control variables I have drawn from relevant research papers and logic too, and they are expected to influence the variation of the dependent variables investigated.

A most reasonable assumption, shared by researchers and habitual soccer fans alike, is expecting greater money to beget greater results. Indeed, most research papers attempt to control for the differing economic might of sport clubs, which, especially in European soccer, and especially in the Premier League does vary to a great degree. Di Domizio et al. (2022) use the size of the hometown of a given team to account for a potential market size and thus source of revenue. Halevy et al. (2012) employed the average pay of players to control for the economic forces behind a team. Bucciol et al. (2014) took the same approach and Hill et al. (2017) included both aforementioned variables as controls. Franck and Nüesch (2011) on the other hand use the absolute wage expenditures. Whilst these are all judicious applications, in my thesis I follow a notably different route. The usage of the population of the home town of a team is quite problematic. For instance the population of Berlin (3.6 million) far exceeds the population of Munich (1.5 million), and even greater is the difference between the population of London (8.9 million) and the population of Manchester (0.5 million), however claiming that the financial might behind the clubs of Berlin or London far outweighs that of the clubs of Munich or Manchester, respectively, is dubious at best, baseless at worst. Average pay or total pay are both better proxies for financial might, yet a team can make a lot of expenditures not directly towards its players that contribute to its success. Better training facilities, equipment, academy, medical teams and analysts are all potentially helpful investments to increase sporting success. Therefore, in this thesis I use the total revenue of teams from their annual financial statements to form a better understanding of the financial might that stands behind the teams. This data was available through the *www.gov.uk*, where all UK based companies have to report their accounts. The control variable is called financial_might. Nevertheless, I also included the most frequently used control variable for economic power, average_pay in the model.

Sometimes success does breed success, thus to control for the effects of this potential performance trajectory I used the league placement of the last season. Previous performance may strongly influence performance in the next season (Hill et al., 2017, p. 1941). I transformed this variable for it to intuitively function and the higher numbers thus indicate better positions (20 equals first place, 19 for second place,...). I named it past_performance. The three teams that were promoted in each season were treated had they reached the last three places of Premier League in the previous season, with the team winning the Championship being assigned to place 18, the runner-up of the Championship to place 19, and the last team to qualify to 20 (consequently receiving scores of 3, 2 and 1, respectively).

In the research model I controlled for the experience the coach has with the team, coach_tenure (Bucciol et al., 2014) and also for the average age of the roster (Di Domizio et al., 2022) and the size of the roster (average_age and roster_size, respectively). Moreover, I included a control variable for league seniority, in order to account for the teams' Premier League experience (Di Betta & Amenta, 2010), counted as the number of seasons a team has competed in the highest of English football leagues (history). Lastly, I utilized the variable average_experience to control for the average amount of years the players of a club have played in the Premier League.

A concise overview of all the dependent, independent and control variables is shown in Table 1, containing the names, definitions and sources of each of them.

3.2.4. Summary statistics

Summary statistics of all variables are reported in Table 2. The dataset contains a 100 observations throughout the five seasons. Altogether data stems from 28 different teams and 14 teams have competed in all five of the seasons investigated.

Table 1: Variable overview

Variable	Definition	Source
DEPENDENT		
team_performance	absolute number of points collected by team *i* at the end of season *t*	www.premierleague.com
cooperation	total number of passes completed by the players of team *i* throughout season *t*	www.premierleague.com
aggressivity_f	total number of fouls committed by the players of team *i* throughout season *t*	www.premierleague.com
INDEPENDENT		
pay_dispersion_gini	Gini index describing the dispersion of players' salaries in team *i* in season *t*	
pay_dispersion_cov	coefficient of variation describing the dispersion of players' salaries in team *i* in season *t*	
CONTROL		
financial_might	total revenue of team *i* reported in the financial statement of the fiscal year *t*	www.gov.uk
average_pay	the mean of players' salaries in team *i* for season *t*	www.spotrac.com
past_performance	the number indicating the league placement of team *i* in season *t-1*, corresponding in reverse order, for the larger numbers to indicate higher placements	www.premierleague.com
coach_tenure	the number of seasons the coach in charge of team *i* has spent with team *i* till the end of season *t*	www.transfermarkt.com
average_age	the mean of players' ages in team *i* in season *t*	www.transfermarkt.com
roster_size	the number of players team *i* has in season *t*	www.spotrac.com
history	the number of seasons team *i* has played in the Premier League by the end of season *t*	www.premierleague.com
average_experience	the mean of the number of seasons each player of team *i* has played in the Premier League till the end of season *t* (not necessarily as part of team *i*)	www.transfermarkt.com

On average, the teams succeeded in collecting 52 points in a season, whilst completing more than 17,400 passes and committing more than 220 fouls. The mean of the variable history is quite high, signifying that most teams have taken part in the highest league more than 17 times. Interesting is, that the median of the variable coach_tenure is but 2 seasons, which speaks for the rarity of coach longevity in the Premier League. The mean is considerably higher, yet this is due to outlier extreme values (e. g. Arsene Wenger has spent 22 years coaching Arsenal).

Notably, there is a vast difference between the minimum and maximum values of the variable financial_might. 26.4 million and 627.1 million stand on the two ends of the scale (more than 0.6 billion difference), which further showcases the variety in the extent of the economic power standing behind a team. The average of the Gini index is 0.325, and it ranges from 0.139 to 0.518 in the dataset. Normally, the Gini index has a range between 0 and 1-(1/n), but the bias-corrected version does range between 0 and 1, with the higher values being associated with greater disparity.

All in all, the descriptive statistics tell that the variables do show sufficient variation, which is a necessity for performing regression analysis. The further imperative assumptions of linear regression will be discussed in the next sub-section.

3.3. Assumptions of linear regression

To be able to use the OLS (ordinary least squares) method for estimating the models of the three dependent variables (team performance, cooperation, aggressivity) certain assumptions need to be investigated first. To test these assumptions, and to calculate the linear regression models later on, I used two different softwares designed for statistical data analysis, JMP and STATA.

Firstly, regression analysis requires a complete selection of relevant exogenous variables. As most real life phenomena is a result of processes of great complexity, naturally utter completeness of a model is impossible, even on a theoretical level. Nevertheless, I selected the variables after careful examination of scientific practice in research papers akin to my thesis, and the presence of these variables is supported by logic too. Thus the models should be deemed as sufficiently complete. Due to the nature of data collection, systematic measurement errors are quite unlikely. Furthermore, as mentioned above the variables show significant variation (see Table 2).

I calculated the correlation between all independent and control variables in order to detect multicollinearity. This was a necessity as high correlation between independent and control variables might render the regression model

Table 2: Descriptive statistics

Variable	Mean	Median	Std. dev.	Min	Max
DEPENDENT					
team_performance	52.670	49.500	18.511	16	100
cooperation	17,447.510	16,541	3,884.648	10,226	28,241
aggressivity_f	222.520	223	27.499	161	307
INDEPENDENT					
pay_dispersion_gini	0.325	0.329	0.076	0.139	0.518
pay_dispersion_cov	0.602	0.601	0.157	0.250	1.161
CONTROL					
financial_might	246,152,601	173,462,500	157,825,173	26,400,000	627,122,000
average_pay	2,965,710.700	2,561,033.300	1,606,817.600	729,955.560	7,660,178.600
past_performance	10.500	10.500	5.795	1	20
coach_tenure	3.110	2	2.964	1	22
average_age	25.773	25.661	1.173	23.409	29.158
roster_size	25.020	25	3.012	17	32
history	17.490	21	9.869	1	30
average_experience	4.673	4.960	1.394	1.222	8.095

strongly biased. The correlation matrix can be found in Table 3. Four control variables showed strong correlation between themselves, history, financial_might, average_pay and past_performance. Between these four all pairwise correlations exceeded 0.6. As financial_might was expected to have the strongest influence on sporting success, I removed the other three from all the models. Now, none of the independent or control variables showed a correlation exceeding 0.6 between each other (with the highest value being 0.531 between average_experience and average_age, and all other correlations being under 0.5). Moreover the Variance Inflation Factors (VIF) were all under or barely above 2 (Mean VIF = 1.49). Therefore going forward the issue of multicollinearity is solved and it does not hinder the models any further.

To test the linearity of the parameters I employed Ramsey's Regression Specification Error test (RESET). The RESET test tests whether the inclusion of nonlinear combinations of fitted values improves explaining the variation of the dependent variable (Volkova & Pankina, 2013, p. 265). In my dataset the RESET test was not significant for team performance and cooperation, with p-values of 0.725 and 0.783, respectively. Unfortunately, for aggressivity the RESET test was significant with a p-value of 0.017. For this model the functional values were likely not defined correctly. In situations like this a possible solution could be transforming the variables, and this I indeed attempted. As the RESET test still remained significant after x^2-, x^3-, and log-transforming the independent variable, I will not handle this issue further in this thesis. The results of the models for aggressivity however, need to be viewed with this knowledge in mind.

Furthermore, for linear regression the error terms need to be normally distributed. This tends to be an issue mostly with smaller sample sizes, nevertheless I performed skewness and kurtosis tests in STATA (called *sktest*). The skewness and kurtosis tests were not significant for any of the models, with retaining p-values of 0.336 (for team performance), 0.733 (for cooperation) and 0.191 (for aggressivity). Thus the non-normality of residuals is not a concern for the regression models.

Next, the assumption of homoscedasticity had to be tested. Homoscedasticity means the absence of heteroscedasticity, thus assumes a constant variance of the residuals. To test for heteroscedasticity (the variance of the residuals being not constant) I performed the Breusch-Pagan test for the models. Neither for team performance (p-value = 0.110), nor for aggressivity (p-value = 0.130) was the Breusch-Pagan test significant, however it was significant for cooperation with a p-value of 0.001. Fortunately, STATA offers a command (called *vce(robust)*) to use White's heteroscedasticity-corrected standard errors, also known as robust standard errors. These robust standard errors will be used onwards to estimate the regression models for cooperation.

Testing for autocorrelation proved non-trivial, as the dataset was not a normal time-series dataset, but panel data, containing a multitude of short time-series independent from one another. Therefore neither the commonly employed Durbin-Watson test, nor the Breusch-Godfrey test was applicable. In order to test for serial correlation in panel data I used the Wooldridge test recommended by Drukker (2003), after Wooldridge (2002). The Wooldridge test was not significant for team performance (p-value = 0.098), yet it was significant for cooperation (p-value = 0.019) and also for aggressivity (p-value = 0.012). Given the characteristics of my dataset, tackling this issue would be most burdensome, as the number of observations within the panel time series is far too few (in some cases only one or two). Still in a more exhaustive research approach one could attempt to nest the data on a seasonal or club level and proceed with a different regression estimation method. As the presence

Table 3: Correlation matrix of the independent and control variables

Variable	1	2	3	4	5	6	7	8	9
1. pay_dispersion_gini	1.000								
2. history	0.204	1.000							
3. financial_might	0.382	0.667	1.000						
4. average_age	-0.428	-0.296	-0.293	1.000					
5. average_experience	-0.141	0.337	0.223	0.531	1.000				
6. average_pay	0.319	0.729	0.896	-0.205	0.373	1.000			
7. roster_size	0.270	0.072	0.144	-0.035	0.031	0.091	1.000		
8. coach_tenure	-0.129	-0.180	0.045	0.159	0.165	-0.061	-0.009	1.000	
9. past_performance	0.347	0.621	0.812	-0.243	0.403	0.805	0.121	0.089	1.000

of autocorrelation does not automatically render the whole model unusable (though it does make the coefficients not efficient and the confidence intervals biased) I will proceed with the OLS method for all dependent variables.

After examining the necessary assumptions of linear regression and OLS I estimated the regression models to test for the hypotheses derived in the *Theoretical background* chapter of this thesis. The results are reported in the next section.

4. Results

4.1. Hypothesis testing

In my statistical analysis I commenced with examining the models for team_performance, the dependent variable measuring sporting success. First, I ran the model with the five control variables (three control variables were removed from the models, see *Assumptions of linear regression*). The regression model was significant (p-value < 0.001), with an F-value of 48.639 and an R^2 of 0.721 (adjusted $R^2 = 0.706$). Financial_might had a strong significant effect on team_performance, with a p-value below 0.001 and a coefficient of $9.178 * 10^{-8}$, moreover average_age had a significant negative effect at a ten percent significance level, with a p-value of 0.075 and a coefficient of -2,120. The other control variables did not have significant effects on the dependent variable.

Next, I added the independent variable, pay_dispersion _gini, to the model. The expanded model was overall significant as well (p-value < 0.001), with an F-value of 40.700 and an R^2 of 0.724 (adjusted R^2 being 0.706). Financial_might had once again a strong significant effect with a p-value below 0.001 and a coefficient of $9.385 * 10^{-8}$, and the effect of average_age was now significant at a five percent level, with a p-value equal to 0.048 and a coefficient of -2.444. The independent variable, pay dispersion did not have a significant effect on team performance, thus Hypothesis 1 was not supported. The other three control variables remained non-significant.

To examine Hypothesis 2, I estimated the model for the dependent variable cooperation. Once again as before, first only the five control variables were included. For this model I used White's heteroscedasticity-corrected standard errors in STATA (see *Assumptions of linear regression*). The model was significant (p-value < 0.001), retaining an F-value of 49.980 and an R^2 of 0.748 (with the adjusted R^2 being 0.735). The effect of financial_might was strongly significant, its p-value being below 0.001, and the coefficient taking the value of $2.003 * 10^{-5}$. Average_age had a significant negative effect with a p-value equal to 0.027 and a coefficient of -517.016. Coach_tenure had a significant positive effect, with a p-value equal to 0.024 and a coefficient of 109.697. The model showed no significant effect for the other two control variables.

In the next step, the independent variable, pay dispersion was included in the model. Once again the model was computed using robust standard errors. The expanded model remained significant (p-value < 0.001), having an F-value of 40.700. The R^2 had the value of 0.750 (adjusted R^2 being 0.733). The influence of the variable financial_might was still strongly significant, with a p-value smaller than 0.001 and a coefficient of $1.972 * 10^{-5}$. The control variable average_age showed a significant negative effect, having a p-value of 0.044, with a coefficient of -468.690. Coach_tenure remained significant as well with a p-value of 0.018 and a coefficient of 114.828. The other two control variables had still no significant effect on the examined construct. Given that in the model pay dispersion the independent variable, did not have a significant effect, Hypothesis 2 remained unsupported.

At last I tested for Hypothesis 3, estimating a regression model explaining aggressivity_f as the dependent variable. The model containing the five control variables was significant (having a p-value of 0.047) and had an F-value of 2.347. The value of R^2 took 0.111 (with the adjusted R^2 being 0.064). The variable coach_tenure had a significant negative effect with a p-value of 0.011 and a coefficient of -2.372. None of the other control variables showed a significant effect.

Including the independent variable pay dispersion in the model proved to be a remarkable improvement. The expanded model was significant (with a p-value of 0.010) and had an F-value of 3.040. The R^2 was considerably higher than previously, now retaining a value of 0.164 (adjusted R^2 = 0.110). Coach_tenure still had a significant negative effect with a p-value of 0.019 and a coefficient of -2.156. Furthermore, now financial_might also had a significant negative effect with a p-value equal to 0.039 and a coefficient of -4.292 * 10^{-8}. The other control variables remained non-significant. However, pay dispersion did have a significant positive effect on the dependent variable, with a p-value of 0.017 and a coefficient of 100.632. Consequently, Hypothesis 3 was supported by the model.

The results of the regression analysis are summarized in Table 4. Model 1, 2 and 3 correspond to the dependent variables team performance, cooperation and aggressivity, respectively. I reported the values only for the models including the pay dispersion, for the table to serve as overview for hypothesis testing. The coefficients are unstandardized and the standard errors are reported in the brackets.

To offer a brief summary of my endeavors for direct effect testing, I have to state, that the models provided mixed results. Hypotheses 1 and 2 were not supported by the regression analysis, therefore no significant effect could have been determined for pay dispersion to influence the performance of teams or their displayed degree of cooperation. Consequently, according to my regression analysis, sporting success and cooperative behavior does not significantly vary between soccer teams, who take vastly different approach in allocating the salaries among their players. However, Hypothesis 3 was supported by the analysis, and pay dispersion had a significant positive effect on the examined dependent variable, aggressivity. This result means, that indeed, higher pay dispersion tends to lead to an overall more aggressive tone within a given team, resulting in a greater number of fouls committed on the field. Among the control variables one that remarkably stood out was financial might, for it had a strong significant effect throughout all three models, undoubtedly testifying for the pivotal role economical power plays in the sport of soccer.

As the results of the models were less than satisfactory, particularly for Hypotheses 1 and 2, and as one control variable showed far greater dominance than any other variable, I decided to conduct further analysis. Therefore, an examination of the possible relationship between the independent variable and the control variable financial might follows in the second half of this chapter.

4.2. Supplemental analysis

The relationship between two variables in management research in particular, and quantitative research in general, is oftentimes dependent upon a third variable. These third variables are called moderating variables and they might exert great influence on the nature or strength of a relationship of two (or more) other variables, or on both (Dawson, 2014, p. 1). As after the theoretical research, and the eventually supported Hypothesis 3, I still firmly believed that the independent variable pay dispersion does need to have an influence on the dependent variables of the Hypotheses 1 and 2 (team performance and cooperation), I decided to conduct tests for moderation effect. My conjecture was that the most dominant control variable of my regression models, financial might, could potentially affect the relationship between pay dispersion and the dependent variables. Therefore, I decided to test for these interaction effects in Model 1 and 2.

In order to operationalize this endeavor, I relied on Jeremy Dawson's (2014) most helpful article, which extensively covers moderation in management research. As I strived to examine the interaction between one independent (pay dispersion) and one moderator variable (financial might) I tested for simple two-way interaction. In order to test for two-way interaction an interaction term needs to be included in the simple OLS regression model. For the interaction term I computed a new variable in JMP. In line with Jeremy Dawson's recommendation I mean-centered the two variables first, the two components of interaction. Mean-centering a variable means subtracting the mean from its values, thus creating a new variable with a mean value equal to zero. The interaction term is calculated then as the product of the mean-centered independent variable and the mean-centered control variable. I called this new interaction variable gini_x_financial_might. The interaction term itself shall not be mean-centered, and the dependent variables remain in their raw forms as well (p. 2). Using the method of mean-centering over others (e. g. z-standardization) is beneficial, as thus regression coefficients may be interpreted directly for the original variables. Jeremy Dawson strongly advises to mean-center all other control variables included in the model as well (p. 12). Consequently, in the coming models all variables, barring the dependent and the interaction, appear in their mean-centered forms. In order to interpret the results it is fundamental to include the main effects of the independent and control variable in the model, besides the interaction term (p. 2).

Thus the expanded regression model is as follows:

$$\begin{aligned} Y = \beta_0 + \beta_1 * \textit{pay dispersion c} + \beta_2 * \textit{financial might c} \\ + \beta_3 * \textit{interaction term} + \beta_i * \textit{control variables c} + \varepsilon \end{aligned} \tag{6}$$

where,

- Y = dependent variable (team performance or cooperation)
- β_0 = the intercept
- β_1 = coefficient associated with the measure of pay dispersion, here the Gini index or the coefficient of variation
- pay dispersion c = independent variable, the Gini index or the coefficient of variation, mean-centered
- β_2 = the coefficient associated with financial might
- financial might c = moderator variable, mean-centered
- β_3 = coefficient associated with the interaction term
- interaction term = product of the mean-centered independent variable (pay dispersion) and the mean-centered moderator variable (financial might), not mean-centered itself

Table 4: Estimation results of linear regression models

	Model 1	**Model 2**	**Model 3**
Constant	93.309*** (31.583)	26,775.88*** (6,305.958)	282.040*** (81.690)
pay_dispersion_gini	-16.038 (16.027)	2,385.367 (2,672.962)	100.632** (41.458)
financial_might	9.385×10^{-8}*** (7.903×10^{-9})	1.970×10^{-5}*** (1.980×10^{-6})	-4.292×10^{-8}** (2.044×10^{-8})
average_age	-2.444** (1.219)	-468.690** (229.433)	-2.775 (3.154)
average_experience	1.347 (0.966)	-294.697 (196.669)	1.915 (2.499)
roster_size	-0.098 (0.350)	-74.329 (73.405)	-0.497 (0.905)
coach_tenure	0.201 (0.348)	114.828** (47.807)	-2.156 (0.901)
R^2	0.724	0.750	0.164

Notes: There were a 100 observations included in all the models.
Robust standard errors were used for Model 2.
Statistical significance levels: * = 10%, ** = 5%, *** = 1%

- β_i = coefficients of the control variables
- control variables c = control variables average age, average experience, roster size and coach tenure, all mean-centered
- ε = error term

Thus I estimated this improved regression model of Equation 6, and tested first for team performance. The model was significant (p-value < 0.001) and had an F-value of 40.807. It had an R^2 of 0.756 (adjusted R^2 being 0.738). This seems to be an improvement compared to the previous model for team performance that did not have the interaction term included (R^2 was 0.724, and the adjusted R^2 was 0.706). In this model the control variables did not have a significant effect on team performance. However, the interaction between pay dispersion and financial might proved to be significant, with the interaction term having a p-value of 0.001, and a coefficient of $-3.738 * 10^{-7}$. My conjecture regarding the presence of a moderation effect therefore found support. The significant presence of the interaction term means, that the relationship between team performance and pay dispersion varies given the level of financial might (see Dawson, 2014, p. 3). A summary of the results of this model can be found in Table 5, along with those of the expanded Model 2.

In order to gain a better understanding of this significant interaction, I used the Excel template offered by Jeremy Dawson at his webpage, *http://www.jeremydawson.com/slopes.htm*. Entering the required data, unstandardized regression coefficients, means and standard deviations, the template plots the effect and visualizes it in a graph. This graph for the expanded model of team performance can be seen in Figure 1.

At the very first glimpse it is striking that the lines associated with low and high financial might have opposing steepness. The figure shows that the relationship between team performance and pay dispersion is positive when the financial might of a team is low. On the contrary, for teams of high financial might, the relationship between team performance and pay dispersion appears to be negative.

As the significance of the interaction term in the model only tells about the existence of a divide between low and high values of the moderator, and not about the significance of the relationship between the independent variable and the dependent variable within these groups, I performed simple slope tests to gain further insight (Dawson, 2014, p. 3). The simple slope tests can be computed with the Excel template of Dawson, used for the visualization in Figure 1. Adding the variance of the coefficient of the independent variable and the moderator, and their covariance of coefficients, I calculated the simple slope tests for the slopes plotted on Figure 1, which are one standard deviation above and below the mean of the moderator variable. The simple slope test for the group of low financial might showed that the slope, as observable, has a positive steepness of 28.889. The test was not significant at a five percent significance-level, with its p-value being 0.150. The t-value of the slope was 1.453. On the other hand, the simple slope test for the group of high financial might was significant, with a p-value of 0.001. The slope had a t-value of -3.446 and a negative steepness of -89.101.

This means, that for teams of high financial might pay dispersion does have a significant negative effect on team performance. The plotted slopes (Figure 1) hint at a weak positive relationship between pay dispersion and team performance amidst teams of low financial might, however this effect is not significant.

For the next step, I tested the interaction model presented in Equation 6 for the second dependent variable of my re-

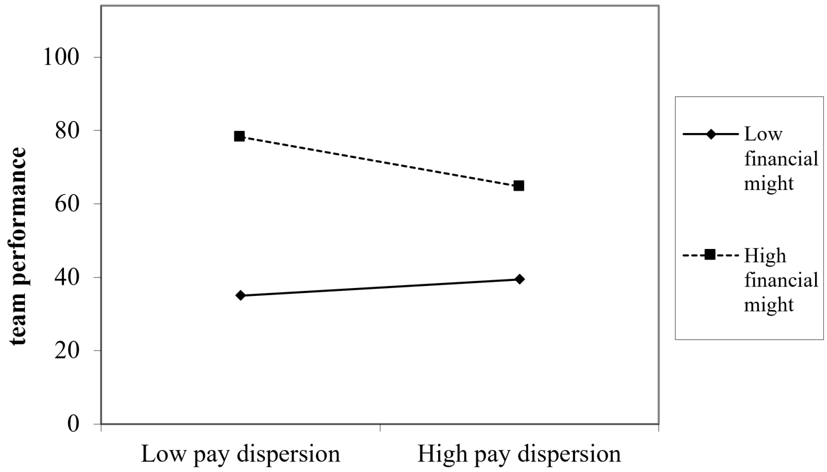

Figure 1: Moderating effect of financial might on the relationship between pay dispersion and team performance

search, cooperation. As before, to control for heteroscedasticity I computed the model using White's heteroscedasticity-corrected standard errors in STATA. This new model was significant as well (with a p-value below 0.001), and had an F-value of 36.680. The R^2 was 0.763 (with the adjusted R^2 taking the value of 0.745). Compared to the previous model for cooperation, where the interaction was not included, the R^2 appears to increase. It had the previous value of 0.750 (and adjusted R^2 was 0.733). Out of the control variables coach_tenure had a significant positive effect, with a p-value of 0.012 and a coefficient of 115.647. Moreover, average_age did have a, now weak, significant effect (only at a ten percent significance level), with a p-value equal to 0.087, and a coefficient of -383.985. Much like earlier, the other two control variables showed no significant effects. Significant was however the interaction term with the p-value of 0.011, and the coefficient of -0.001. This proves that, as with team performance in the expanded Model 1, the moderating variable, financial might, does influence the independent variable's relationship with cooperation. Given the values of financial might, there is significant difference between the relation of pay dispersion and cooperation within a team. For an overview of the results of this model see Table 5.

To attain an apt presentation of the interaction effect, I again relied on Jeremy Dawson's Excel template, to visualize the two-way interaction between pay dispersion and financial might, this time for cooperation. This visualization may be found in Figure 2.

Figure 2 shows much similarity to Figure 1 at first observation. The lines depicting the groups of low and high financial might have opposing steepness. It appears that for teams of lower financial status pay dispersion increases the number of passes and thus cooperation. On the other hand, pay dispersion within teams of higher financial status seems to have an adverse effect on cooperation.

As before, the significance of the interaction term within my model, and the plotting of the slopes in Figure 2, only testifies for the existence of a significant difference between the two groups, determined as one standard deviation above and below the mean of the moderator variable (high and low financial might, respectively). Therefore I performed simple slope tests to test for the significance of the individual relationships.

The results of the simple slope tests were the following. For the group of teams characterized by high financial might the slope had a steepness of -7515.308. The simple slope test was not significant for this group, having a p-value of 0.132. Its t-value was -1.520. The slope of the low financial might group had a positive steepness of 8474.292. Contrary to the test for the high financial might group, this simple slope test was strongly significant with a p-value of 0.007. The test's t-value equaled 2.745.

Testing for the interaction effect in the models of the second dependent variable showed that there is a significant difference between how pay dispersion affects cooperation given the level of financial power. The simple slope tests allowed a deeper understanding of this finding. Their results suggested, that within teams of high financial status pay dispersion does not significantly influence the level of cooperation, albeit the visual plotting of the slope implies a weak negative relationship (Figure 2). Yet, for teams of low financial status pay dispersion does indeed have a significant positive impact on the level of cooperation displayed.

Albeit the original hypothesis did find support in Model 3, I also tested for the presence of interaction for the third dependent variable, aggressivity. Although the expanded Model 3 was significant (having a p-value of 0.015), the interaction term itself was not significant, with a p-value of 0.522. Therefore, I did not investigate in this direction any further.

For robustness check I have calculated every test and model using the coefficient of variation as the independent variable pay dispersion, instead of the Gini index. The calculations were robust, with the tests (assumptions of linear regression) being significant precisely where they were with the Gini index and being non-significant in synchron

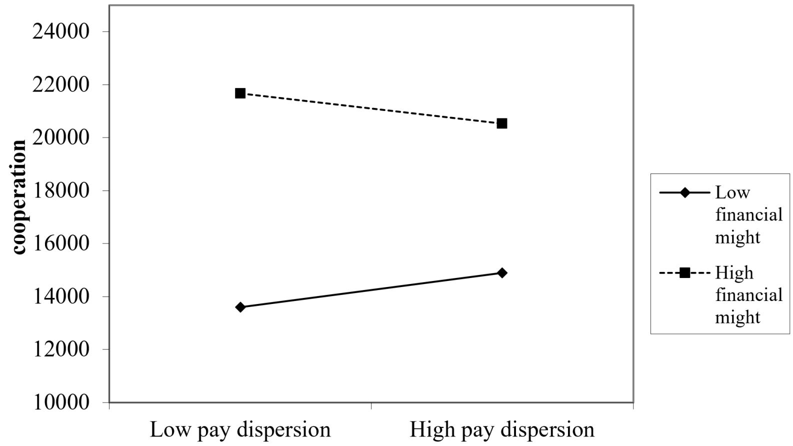

Figure 2: Moderating effect of financial might on the relationship between pay dispersion and cooperation

Table 5: Estimation results of the expanded linear regression models

	Model 1'	**Model 2'**
Constant	54.361*** (1.065)	17676.580*** (212.782)
interaction_term	-3.740×10^{-7}*** (1.070×10^{-7})	-5.060×10^{-5}** (1.960×10^{-5})
average_age	-1.819 (1.166)	-383.985 (221.825)
average_experience	1.281 (0.913)	-303.709 (194.530)
roster_size	-0.110 (0.331)	-76.003 (73.549)
coach_tenure	0.207 (0.329)	115.647** (45.297)
R^2	0.756	0.763

Notes: There were a 100 observations included in all the models.
The coefficients are unstandardized and the standard errors are reported in the brackets.
Robust standard errors were used for Model 2'.
Statistical significance levels: * = 10%, ** = 5%, *** = 1%

with the Gini index. Estimating the models retained largely the same results considering when variables were significant and at what significance level, with three small discrepancies. Firstly, in the regression model testing for pay dispersion's direct effect on team performance (Model 1), the control variable average_age was only weakly significant for the coefficient of variation model, with a p-value of 0.056. This small divergence may be deemed inconsequential for my thesis. Far more interesting is however, that using the coefficient of variation not only replicated, but even strengthened the findings surrounding the interaction effects, particularly the simple slope tests. As with the coefficient of variation, for both interaction models, both slopes were significant. As in, for team performance pay dispersion had a weakly significant positive effect on the low financial might teams, with the p-value of 0.051 (t-value 1.977, steepness 19.846). For cooperation pay dispersion had a weakly significant negative effect on the high financial might teams, having a p-value of 0.095 (t-value -1.687, steepness -3606.326). Therefore my findings can be considered robust, and employing the coefficient of variation even confirms effects (at a 10% significance level) that were only surmised with models of the Gini index.

In the next chapter follows a discussion of the results of my analysis.

5. Discussion

5.1. Theoretical implications

The findings of my thesis offer insight into how pay dispersion influences team effectiveness in soccer teams. My results showed, that at large the effectiveness and outcomes of teams are related to pay dispersion, however this relationship might be moderated by another variable in certain aspects. The presence and conspicuous nature of this moderating effect is what could be considered the chief contribution of my thesis to scientific literature studying hierarchical differentiation and team effectiveness. In sport setting in particular and in management environment in general.

Albeit the influence of hierarchy on the effectiveness of organizations and groups is highly debated, lately the consens has somewhat shifted in the direction of hierarchy and hierarchical differentiation being a detriment to positive outcomes (Greer et al., 2018). When testing for the direct effect of pay dispersion on team performance, my regression analysis showed no significant effect, and consequently Hypothesis 1 was not confirmed. This, to a certain degree contradicts both the studies that argued for an improving influence of hierarchy (such as Halevy et al. (2011), Kampkötter and Sliwka (2018), Ronay et al. (2012), and To et al. (2022)), and also the ones proclaiming adverse effects of hierarchy (such as Hays et al. (2022) or Greer et al. (2018)). This unexpected, and at first glimpse somewhat unsatisfying, outcome can be explained by the presence of a strong control variable (financial might) and its imposed interaction on pay dispersion. The results of the interaction analysis showed, that pay dispersion has significantly different effects on team performance given the degree of financial might, i. e. economical power behind the team. For the economically more powerful teams pay dispersion had adverse effects on sporting success, thus confirming the unified findings of the meta-analysis of Greer et al. (2018). For the economically less mighty teams the effect, albeit appearing slightly positive, was not significant in nature (for the Gini index, though weakly significant for the coefficient of variation), therefore the results of my thesis do not primarily support the row of studies arguing for hierarchy breeding success.

What stands behind this separation of effects is a compelling question and cannot be answered with utter surety based on my conducted research alone. Yet, one possible explanation I would propose here. The economically less powerful teams are usually the teams on the lower end of the Premier League rankings, thus the main concern for such teams is to avoid relegation and carve themselves a deserved and stable place in the highest of English soccer leagues. For teams like that having ‘star players’, differentiated from the other players with a disproportionately higher salary, might very well be regarded as means for attaining a much needed legitimacy. The presence of one or two such top players, separated in status, signals the belonging of a club to the Premier League (which is a primary concern of smaller clubs, as the competition is hard with a high profile second league below them, the Championship), and therefore likely be viewed more positively by other team members, as it contributes to a common and strongly desired end. And for that end it is likely recognized as a necessity, and less likely causes internal tension and conflict, which would considerably hamper team performance. On the other hand, for the economically powerful teams, as the ‘Big Six’[1], relegation and attaining sporting legitimacy is of no relevant concern, and their endeavors are largely directed towards winning trophies and qualifying for the Champions League. Now, such teams possessing great financial might are likely constituted from top-class players, who all were or could have been regarded as ‘star players’ in their respective carreers, yet even among them salary differences do and will occur. I believe a major psychological contributor to the negative impact of pay dispersion on the performance of economically powerful teams could be the greatly increased tension. As in this case the positive aspect of increasing a team’s status and legitimacy is virtually absent, as is the fear of relegation, and at the very same time ‘star players’ are selected (due to great differences in absolute salaries) among players who all, and maybe even rightfully, consider themselves ‘star players’. Differentiating between players who mostly find themselves quite worthy of eminence may easily create tension, and without the alleviating circumstance of, for lack of a better word, fighting for survival in the Premier League, this internal tension can cause detrimental consequences on sporting success. This is but a theory, and it may be interesting to investigate the possibility of this psychological connection. For that end, conducting deep interviews with players might be a necessity.

Hays et al. (2022) argued in their study for how hierarchical differentiation decreases cooperation within teams, through increased competition, and Greer et al. (2018) found as well that cooperation decreases as a result of increased differentiation through the birthing of more and severer conflicts. Testing for direct effect on cooperation, I found no significant effect in my regression analysis, thus neither Hypothesis 2 was confirmed. This appeared to contradict the theoretical background of my research, as null-effect was scarcely, if ever, theorized, yet once again testing for interaction effects helped to shed light on the multifaceted nature of this relationship. Financial might indeed influenced the relationship between pay dispersion and cooperation, and there was a significant difference between the high and low financial might clubs. For the economically more powerful clubs pay dispersion appeared to decrease cooperation, yet the effect was not significant (for the Gini index, but weakly significant for the coefficient of variation). For the economically less powerful clubs however pay dispersion improved cooperation. This finding, for the low financial might clubs, supports the findings of Halevy et al. (2011), where they argued for an increased voluntary cooperation and contradicts the studies of Greer et al. (2018) and Hays et al. (2022).

Explanations for this dual nature of the relationship between pay dispersion and cooperation could follow a similar line of argumentation as for team performance (see above). It even supports the previous argumentation, as it shows a significant improvement in cooperation for the highly differentiated, yet economically less powerful teams. In other words, it appears that elevating the status of players, or ‘creating superstars’, might be rewarded with a positive echo from teammates if they recognize it as a pivotal step for achieving the club’s goals. And similarly as before, it is notable that this positive impact is absent for high financial might teams. The parallelisms in findings and possible explanation schematas for team performance and cooperation are unsurprising as these two markers of team effectiveness themselves are highly correlated with each other. In my dataset the correlation of the variables team effectiveness and cooperation was 0.822.

Though it is not an overmuch studied relationship I theorized that pay dispersion does affect the aggressivity of a team. Testing for this direct effect my regression analysis showed a significant positive effect of pay dispersion on aggressivity, thus Hypothesis 3 was confirmed. The way it was modeled this finding means that the higher the dispersion in salaries the more explicit aggressive acts will be committed

[1] The term ’Big Six’ refers to the six most dominant clubs of the Premier League during and after the 2010s. In alphabetical order they are: Arsenal F. C., Chelsea F. C., Liverpool F. C., Manchester City F. C., Manchester United F. C. and Tottenham Hotspur F. C.

by the team members. My research investigated solely aggressive acts directed outwards from the team and towards the opponent (as fouls were used as proxy), therefore this positive association shows that within-team pay dispersion increase may result in enhanced between-teams aggression. The connection between aggression and pay dispersion might be explained by the increased within-team competition. Hays et al. (2022) showed that pay dispersion increases competitive behavior and there are studies linking competitiveness and aggressive behavior together, such as Dumblekar (2010), Krisnadewi and Soewarno (2020), and Schmierbach (2010), all showing positive effect. Albeit the Hypothesis 3 was confirmed I tested for the presence of an interaction effect with financial might as before, yet no such significant effect was found. Financial might itself however did have a significant negative effect on aggressivity, which may not be as surprising as most fouls are committed whilst defending, therefore teams who spend more time attacking and making plays will naturally commit less fouls.

Considering studies that examined pay dispersion within sport settings, my research contradicts Halevy et al. (2012) (basketball) and Hill et al. (2017) (baseball) as both showed positive relationship between pay dispersion and team performance. As Hill et al. investigated baseball teams, this may be attributed to the stark differences between a soccer and a baseball game, with baseball teams relying much less on cooperation, and baseball being overall a sport where outstanding individual performances might amount to great sporting success, whereas in soccer not so much or far more rarely. The divergence from Halevy et al.'s study is not as straightforward to explain, yet it might be due to the different team sizes (5 for basketball vs 11 for soccer), and overall smaller pitch, which results in tighter interplay between team members, where a hierarchical figure might exert greater influence upon the team, and coordination benefits are easier to reap. Yet again, my knowledge of the game of basketball is not sufficiently deep to wholly explain this discrepancy. On the contrary my research did confirm, leastwise for the high financial might teams, the results of Mondello and Maxcy (2009) (football), as they argued for pay dispersion diminishing team performance.

For studies analyzing soccer teams, Franck and Nüesch (2011) showed a U-formed relationship between pay dispersion and team performance. Although the corresponding tests were attempted, I did not find proof of such a U-formed or other nonlinear effect in my data. The results of the study of Bucciol et al. (2014) were to some extent confirmed however, as they predicted a negative relationship between pay dispersion and team performance, although only for the part of the team active on the pitch. Bucciol et al. (2014) moreover argued that the decreased performance is not due to decreased cooperation, which my analysis, again partially, supports, as for the low financial might teams pay dispersion did indeed increase cooperation, and for the high financial might teams it did not decrease it significantly. The results of my thesis also support the findings of Di Domizio et al. (2022), as they showed that the financially mightier teams perform better in terms of seasonal success. They derived this from using relative wages to control for financial power, whereas I used the total revenue, which two measures do correlate, but under no circumstance can be understood as the same. Furthermore, Di Domizio et al. found a significant negative association between pay dispersion and team performance, which my thesis also determined, albeit only for the financially mightier teams.

A cardinal difference between my thesis and most papers investigating the effects of pay dispersion using sports data, was the chosen control variable financial might and how it was defined. Money is a force of great magnitude in professional sports, therefore to aptly control for it is paramount. As argued in the *Methodology* section I find the usage of market size, as in the population of a given team's hometown (see Di Domizio et al. (2022) or Hill et al. (2017)), suboptimal to say the least, as it vastly downplays the economic power of some of the biggest clubs (e. g. Manchester City or Liverpool). Employing average or total pay is a far more accurate approach (see Bucciol et al. (2014) or Franck and Nüesch (2011)), yet I believe neither that would be the optimum, as several expenditures may contribute to a team's success aside from those directed towards the players, such as medical teams, analysts or training facilities. Consequently, I employed total revenue or group turnover. This variable did indeed prove to be strongly significant throughout all the models, moreover it helped to shed light on the interaction effect between financial might and pay dispersion. The interaction effect, which may be accredited as the main contribution of my present thesis, and which according to my best knowledge, and as of writing this thesis, was not thus far examined.

At last considering the other control variables, their impact could be determined as mixed at best. Whilst average age and coach tenure were significant in some of the models, notably both of them in models estimating cooperation (original and expanded too), the other control variables were far less impactful. Average experience and roster size were not significant in any of the models, neither in those that tested for direct effect, nor in the ones that estimated interaction. This means that the experience the players have collected in the Premier League is not a significant determinant in how the team will fare in competition or how strongly the players will cooperate, moreover that the size of the roster is largely inconsequential for success and cooperation. Less surprising is, that neither of these factors affect aggressivity. Nonetheless this result propounds the question whether there is any merit in their inclusion as controls in further studies investigating pay dispersion in professional sports.

5.2. Practical implications

My research offers some important practical implications for managers. Based on my findings, an approach to salary distribution should most definitely take into consideration the overall economic or financial power standing behind a team, as the effects of pay dispersion do impact differently the team's performance given the magnitude of financial might. In organizations or teams of high financial power, pay dispersion adversely affects team performance, thus it should be opted for a more egalitarian pay structure. Whereas in a lower financial power setting, pay dispersion weakly, and not significantly, but improves performance. In other words, for instance within the very same organization, it might be prudent to differentiate in pay levels on the lower echelons of the organizational ladder, e. g. teams of low-level operational tasks, but at the same time prioritize even distribution of salaries within the upper management teams and executives. It may be beneficial to that wise communicate the possibility of hierarchical ascension at the lower levels of the organization, yet emphasize the notion among the highly ranked employees that they are valued nigh equally within the organization. Creating 'superstars' or star employees may as well function as a driving force in teams of lower hierarchical standing, but it will cause tension and conflict in teams or groups where everyone, or most, consider themselves as an illustrious member of the organization and a major contributor to its successful functioning and past achievements.

Similarly, pay dispersion exerts opposing influence on the cooperation of teams, once again given the surrounding financial might. Managers shall be mindful that among highly paid employees (i. e. teams of high financial might), dispersion of pay will not advance cooperation, it might even lightly hinder this type of endeavor. For teams of lesser wage however, differentiated pay might increase voluntary cooperation and cause overall greater individual effort to contribute. A further notable implication is, that pay dispersion and the resulting hierarchical differentiation may increase aggressivity and competitiveness, thus if organizations have to deal with issues caused by aggressive behavior of employees, the differences in pay might be significant contributor to it. Albeit pay dispersion does significantly increase aggressive behavior, it has to be noted, that it is by no means the only, or the primary determinant (given the somewhat low R^2 of the model, i. e. the portion of variance explained), and many other, and especially circumstantial, factors play a role.

5.3. Limitations and future research

At long last certain limitations of my research need to be addressed. First and foremost it has to be understood that the sport setting itself is a very unique environment, and the findings of my thesis shall not be heedlessly adapted. Generalizability is ever the question for research relying on sports data, and not all sports teams are apt models for all organizations or teams. A profound understanding of the sport and the structure of its competing teams is needed in order to truly make use of the implications, for the better of the organization. Here, I recommend reading the paper of Keidel (1987), where he provides guidance for applying knowledge collected from sports in organizational setting. Soccer may be substituted for basketball in Keidel's framework, due to the similarities of the nature of the two games (Keidel, 1987, p. 592).

Using sports data in managerial research is akin to a large scale field experiment, where there are clear rules, boundaries and controls. It delivers compelling and rich data, but it does not perfectly model life. Examining soccer teams shows some peculiarities, which set this environment apart from most business organizations. For instance the salaries are absurdly high compared to normal organizations. Moreover, the players are under near complete public exposure, which rarely happens in the world of business. In my research, the teams I investigated showed no diversity in terms of sex. From one side, conducting a research to test for the robustness of the findings whilst collecting data from female teams should not be overly difficult. Quite difficult is however to find mixed teams, which do not exist in high level professional sports, yet are quite prevalent in organizations.

Similarly, the diversity of age was much smaller in my dataset compared to normal organizations, and individuals far too young to be commonly employed did have a lasting impact on the outcomes of certain teams (e. g. 19 year old Bukayo Saka was a major contributor to Arsenal's 2021/22 season, playing in all 38 games (scoring 11 goals), and so was 21 year old Phil Foden for Manchester City, playing 28 games in that season (scoring 9 goals)). Given the smaller degree of age diversity and the overall low average age of soccer teams, the implications of my research may be even more applicable to start-ups, than to mature organizations. Testing my findings in the setting of start-up organizations might be a promising direction for future research.

Some shortcomings of the collected dataset were revealed whilst inspecting the assumptions of OLS regression. The RESET test was significant for aggressivity, which means the functional values for that model were not perfectly defined. Likely there is a nonlinear relationship between pay dispersion and aggressivity. Models estimating this relationship should try for transforming the independent variable, pay dispersion. Notably however, the squared, cubical and log-transformed versions of the variable did not bring sufficient results, and the RESET test remained significant. Therefore other mathematical transformations may be needed to lift this burden.

Another weakness of the dataset was the presence of autocorrelation. The Wooldridge test was significant for the models of cooperation and aggressivity. To tackle this issue, which is quite difficult due to the panel data being consisted of several short time series (spanning from one to five observations), nesting the data on a seasonal level might offer help. Alternatively using the generalized least squares (GLS) method can prove to be fruitful, as GLS is less prone to be biased by autocorrelation than OLS.

It would be highly interesting to unearth the psychological factors standing behind the interaction effects discovered in my thesis. I theorize that in smaller clubs the players view much more favorably 'superstars', as they recognize the need for their presence, as opposed to bigger clubs where elevating the status of some players begets a negative echo among others. This, however is most difficult to prove by merely relying on quantitative data. For future research, I recommend the collection of qualitative data by conducting deep interviews with players, where they are asked to share their perceptions, regarding the presence of 'superstars' and what it means for their clubs. Incorporating a mixed methods approach in our analysis could advance the understanding of these complex processes.

Regarding my models for aggressivity I do believe that the number of fouls is the best accessible proxy, however it should be viewed somewhat askance. Umphress et al. (2010) coined the term unethical pro-organizational misconduct, where they refer to a specific type of misconduct, one committed intentionally and in order to benefit the organization. Unethical pro-organizational behavior is highly prevalent in professional soccer and its most common form is tactical, or professional, fouls. This is where the line becomes a trifle blurry. Most soccer fans vividly remember the finals of Euro 2020, where, in minute 90+6 Giorgio Chiellini (ITA) grabbed Bukayo Saka's (ENG) shirt lugging him to the ground, thus halting a dangerous outbreak of the striker and sending the game into extra time (after which Italy won the game and the trophy in penalty shootout). This foul hardly seemed an act of uncontrolled aggression resulting from the within-team tension and much more cold calculation, where the benefits apparently outweighed the risks for the perpetrator. However on the contrary, even tactical fouls may indeed result from increased tension and competitiveness within the team, as players sense a higher pressure to perform and advance their teams. To differentiate between acts of aggression and unethical pro-organizational behavior without context is highly difficult, thus the one solution I could recommend, would be closely observing soccer games and evaluating the actions as they unfold.

Further research could examine different facets of hierarchical differentiation, alone or in combination with pay dispersion, on team performance. Seniority on the team, and even position on the field may be a crucial determinant of the social rank order. Moreover, it could be interesting to attempt to replicate my findings, particularly regarding the interaction of financial might and pay dispersion, in other sports with teams of different structure, such as (American) football or baseball.

In conclusion, my findings support the notion that hierarchical differentiation, and pay dispersion in particular, play a pivotal role in the effectiveness of teams. However, my analysis also proved that for sporting success the effect of pay dispersion is contingent upon the financial power standing behind the teams. Similarly, the interplay of financial might and pay dispersion is a strong determinant of within-team cooperation, yet, the overall aggressivity of a team they influence independently and contrarily. I hope for my thesis to inspire future works utilizing soccer data in managerial research.

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