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Master Thesis Industrial Dynamics and Strategy

The Managerial Impact on Team Performance in Professional Sports – A Quantitative Analysis of the German Bundesliga

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Abstract

In this thesis I investigate the impact of managers on team performance by estimating manager fixed effects. Using a dataset that covers the last 11 seasons of the first German Bundesliga, I show that managers have an overall significant impact on their teams' success. Moreover, they have an effect through their individual characteristics and tactical decisions. Despite, my results suggest managers to apply tactical and strategic decisions on the basis of total team values and whether they play at home or away.

Keywords: managerial skills, team performance, European football, fixed effects

1 Introduction

Since the football World Cup in 1938, the German national team always survived the group stage and qualified to the playoffs. However, this year the team coached by Joachim Löw finished at the bottom of Group F. In a nutshell, Germany scored only twice against Sweden and lost against teams that have 20 percent (Mexico) and 10 percent (South Korea) of the total team value compared to Germany.[1] Even though the applied strategy and tactic seemed to be clearly inefficient, Löw kept using them throughout all three matches. Whether the German squad played badly or the other teams had better players, commentators argue that Löw's strategy had a major effect on the results due to his questionable managerial decisions.

The contributing literature for this thesis is indifferent as there is an ongoing debate of whether or not managers[2] have a significant effect on team success. For instance, Kuper and Szymanski (2014) are skeptical about this managerial impact and claim that it is overestimated. Moreover, managers' influence on success has to be differentiated from team success that is based on the financial capacity of clubs to hire better talent (Dawson et al., 2000; Szymanski, 2015). Even though managers do vary in their characteristics (Brady et al., 2008), changing managers does not necessarily improve the performance of a team (Besters et al., 2016; van Ours and van Tujil, 2016). In addition, a majority of analyzed characteristics (e.g., age, nationality, coaching experience) do not influence team success (Mühlheusser et al., 2016). Nonetheless, other results show that managerial fixed effects have an impact on team performance (Mühlheusser et al., 2016; Peeters et al., 2017). According to Frick and Simmons (2008), the organization of the team might be the key skill of managers to affect performance. Therefore, Santos (2014) analyzed strategic choices of managers on a team's success. They found that defensive strategies are less efficient compared to offensive orientations.

[1] Information retrieved from transfermarkt.de. The platform provides an overview of all national teams from the World Cup 2018 and their total team values.
[2] As the title of a team's head-coach differs across countries, sports, and leagues and to avoid confusion, the title 'manager' is used for the first coach or head-coach of a team. Moreover, this title has to be distinguished from the General Manager (GM) of a club. While the manager can be referred to a middle manager of an organization, the GM can be identified as a company's top level executive (Peeters et al., 2015).

In this thesis I examine the importance of managers for team performance. To accomplish this, I exploit data on managers in the first German Bundesliga. My dataset contains information on 3,366 games played in the Bundesliga from season 2007/2008 to 2017/2018. One season consists of 34 matches for each team. I retrieve information such as match statistics and club data and further combine these with my database of characteristics and behavior of Bundesliga managers (e.g., experience, tactical and strategic decisions). Following the approach of Abowd et al. (1999), I evaluate the effect of managers by examining ordinary least squares regressions that include manager and club fixed effects. Further, I investigate the managerial impact by including their personal characteristics and tactical and strategic behavior. For the latter part, I also conduct a multinomial logistic regression model to achieve results for the relationship between individual tactics (team formation) and other time-variant variables (e.g., team values).

I find that managers have a significant impact on team performance. When estimating individual effects, I show that managers of teams placed in the middle of the league table have a larger impact on team performance compared to managers of top teams. This is consistent with the findings of Mühlheusser et al. (2016). In a second step, I analyze characteristics and behavior of managers. I find that the impact of managers on team performance is significant both based on their characteristics and tactical and strategic decisions.

This thesis contributes to the aforementioned literature, as it adds new insights on the impact of managers on team performance through their characteristics and behavior. Moreover, previous analyses use either outdated data (e.g., Mühlheusser et al., 2016), or the data regards different sports (e.g., Peeters et al., 2017). Also, I add new variables for tactical and strategic decisions of managers (e.g., team formation, shots on target) compared to other empirical approaches (e.g., Santos, 2014). In addition, I address the ongoing debate by disentangling the effect of managers from the impact of their respective club and the overall strength of Bundesliga teams.

In the following section I explain the role of football managers. Next, I introduce my created dataset and focus on the empirical approach and the identification of managerial effects on team performance. Section five discusses my results and presents the statistical output for the conducted models. The final section discusses these results and provides concluding remarks.

2 Theory

The owners of modern organizations assign a manager the responsibility for the daily business in exchange for a salary. Typically, the manager then organizes the efficient transformation of the firm's given input into output with the objective to maximize it (Dawson and Dobson, 2002). But by how much does a supervisor or manager improve the firm's and team's productivity? According to Lazear et al. (2015), a replacement of a manager with a better one can increase the total output of his team on average by more than ten percent. Not only does a better manager increase productivity, but workers are also less likely to leave the company.

Furthermore, Bloom and Van Reenen (2007) and Bloom et al. (2014) found that firms differ in terms of performance within and across countries due to qualitative and quantitative differences in management practices. By using data from more than 730 companies from the US and Europe, they observed that better managers have a stronger impact on a firm's performance measured by its productivity, sales growth, profitability and survival. Hence, the performance of the manager is crucial to achieve the company's objectives. Nonetheless, managers cannot be seen as selfless and homogeneous parts of the production input, as a large number of empirical studies of managerial decision-making assume (Bertrand and Schoar, 2003). Managers have their individual style when it comes to operational and strategic decisions and hence, their individual efficiency is likely to vary.

Bertrand and Schoar (2003), Bloom et al. (2014), Dawson and Dobson (2002), and Lazear et al. (2015) found significant impacts of managers on performance. Despite, the economic literature specifically on the topic of managerial impact on a company's productivity is scarce. One reason for that is the difficulty of monitoring a manager's performance as most decisions are not transmitted into output within a short period of time. Moreover, it is uncertain for the firm owner which characteristics can be associated with a favorable performance (Dawson and Dobson, 2002).

As adequately argued by Kahn (2000), the sports sector is an appropriate industry to analyze empirical questions in the field of labor economics and to solve the aforementioned issues. Objectives as well as outcomes in professional team sports are much clearer and universally applicable compared to other industries as teams generally try to maximize their performance. In addition, data of input (e.g., team formation, player values) and output measurements (e.g., scores, wins) are freely available (Frick and Simmons, 2008; Peeters et al., 2015). In particular, characteristics and decisions of managers are widely observable (e.g., in professional football leagues on a match day basis).[3]

Scully's (1994) article on managerial efficiency on professional sports teams marked the increasing interest in the managerial impact on team performance. He found that a manager's term of office is linked to his efficiency and ability to achieve the largest percentage to win while selecting players from a fixed pool of inputs. Ever since, an ongoing debate among researchers started whether managers of professional sports clubs have an impact on their teams' success. As such, Dawson et al. (2000) claim that indirect effects of managers were not considered by a majority of empirical studies as they took only ex post player inputs into account as factors for performance. Still, indirect managerial impacts that could be observed ex ante might influence team performance as well, because a manager's task is also to improve input quality. In addition, just because a manager is successful with his team does not mean that he is also influential. A club that is able to spend more money on players correlates positively with a successful team performance. Therefore, a better performance is not necessarily due to the impact of the club's manager (Mühlheusser et al., 2012; Simmons and Forrest, 2004; Szymanski, 2015). But is it true that managerial decisions only play a subordinated role as Szymanski (2015) claims? Or are clubs with less financial capacity for talent able to beat financial giants in their league through tactical and strategic decisions undertaken by the manager? In other words, is the role of the manager not only to enhance the usage of a fixed amount of playing input but also to improve the quality of it?

In general, a football manager has to perform similar functions compared to his counterpart in business organizations. His main functions are organizing, controlling, planning and leading a team (Dawson and Dobson, 2002). Controlling includes the monitoring and assessment of whether the organization meets its tasks. Leading involves motivating and encouraging staff and players to add their maximum effort to seek the objectives of the club. Both functions indirectly influence the performance of the team

[3] For less confusion and also to refer to the origins of the sports, which trace back to England and Germany (Escher, 2016), I use the term 'football' as the counterpart of the American term 'soccer'.

(Dawson et al., 2000). More importantly, a manager directly affects this performance through organizing and planning the teams' on-field tactics and strategies.[4] As such, he has to pick the eleven starting players for each match from the club's employed player pool (Mühlheusser, 2012). Moreover, the manager has to select a starting formation as a key tactic to defeat the opponent team.

Santos (2014) analyzed matchday data of the European Champions League from 1997 to 2010 to investigate how a managerial choice regarding tactics and strategy affects a team‘s performance by taking its expected points won per game into account. By estimating a principal component analysis (PCA), Santos found that the commonly used defensive play is not efficient and managerial decisions are too conservative when it comes to strategic decisions. Moreover, teams that are more offensive and follow the strategy 'Pressing'[5] to regain ball possession as quick as possible are on average more successful compared to other strategic decisions (Vogelbaum et al., 2014).[6] Nonetheless, a manager's decision for team formation can lose its impact on performance as other clubs could be able to adopt the most successful tactic through labor mobility (Aime et al., 2010).

On the other hand, it is essential for a club's success to acquire the optimal manager (Brady et al., 2008). Appointing the wrong manager can end up being costly. Either the club suffers from bad managerial decisions and loses its attraction to fans and media, or the manager's contract is terminated before it ends and the manager has to be compensated (Bell et al., 2013). Given that costs for appointing the wrong manager are high, the interest and economic literature has extensively examined whether and when a manager dismissal is efficient. Besters et al. (2016) and van Ours and van Tujil (2016) provide empirical evidence that the overall team performance does not improve after a

[4] Unlike in other sports economics articles and books, I distinguish between a manager's tactical and strategic decision. According to Escher (2016) and Wilson (2014), both terms originate from the military and were transferred to football during World War One. While tactics can be defined as the use and organization of equipment and soldiers in war, the definition of strategy involves a detailed plan for obtaining success in settings such as politics or war. In football, a manager's strategy includes overarching objectives (e.g., is shooting goals more important than preventing goals?) and tactical decisions involve elements that are used to realize this strategy. For example, team formation is a key tactical element as it essentially contributes to the strategy.

[5] Due to Escher (2016), 'Pressing' is defined as the creation of tension with the purpose to get the ball back.

[6] Note that Vogelbaum et al. (2014) does not take any endogeneity issues into account. For example, the variable for the strategic decision might correlate with the error term and hence, it is difficult to explicitly determine the effect of a 'Pressing' strategy.

replacement of the manager. Still, it seems to be better to change managers than not acting at all (Besters et al., 2016). But what characteristics define an optimal manager?

In a recent paper, Mühlheusser et al. (2016) analyzed the impact of a manager's professional background and on which position he played. Conducting a set of regression models, they found that managers who were former professional players have on average a significant negative effect on performance compared to their non-professional counterparts. Whether a manager previously played for his national team and his former on-field position provided no significant impact on team success. In addition, Peeters et al. (2017) estimated a two way high-dimensional fixed effects model using matchday data of English league football from 1974 to 2011. They found that managerial ability significantly differs. More precisely, for a quarter of instances of firm hires, rehired experienced managers have a lower ability compared to an average entrant at the moment of hiring. This matter makes the hiring market for football managers less efficient.

3 Data Description

This thesis analyzes data from the first German Bundesliga, one of the economically strongest major leagues in Europe. The league hosts 18 professional football teams that play each other twice per season (home and away), concluding in 34 match days and a total of 306 games per season.[7] Table II in appendix B shows the setting of the Bundesliga.

Moreover, data is observable for players as well as managers on a weekly basis. The dataset covers match day data for 11 seasons from 2007/2008 to 2017/2018, including 3366 matches in total. I gathered data for the club, team, manager, fans, and odds from the two main sources transfermarkt.de and football-data.co.uk. In addition, other sources were cross-checked (e.g., kicker.de, soccer.com, sport1.de) to confirm the reliability of the observed data. Table I in the appendix B provides a definition of the main variables of the dataset.

4 Methodological Approach

4.1 Identification of Manager Fixed Effects

In the first part, I analyze the general impact of Bundesliga managers on team performance. Therefore, the first and fundamental hypothesis is as follows.

H_1: Managers of Bundesliga clubs have an impact on team performance of Bundesliga clubs.

In order to explain a club *i's* performance under manager *j* against an opponent club *k* with its manager *v* for match *t*, I consider the empirical model (1) below.

$$Score\_Diff_{ijkvt} = \gamma_i + \lambda_j + \beta X_{ikt} + \delta_k + \theta_v + \varepsilon_{ijkvt} \quad (1)$$

[7] Since the season 1995/1996, the Bundesliga adopted the Three-Point-Rule from the Fédération Internationale de Football Association (FIFA) (Mühlheusser et al., 2012). Since then, a winning team is awarded three points, while a draw means one point for both teams, and a losing team is awarded with zero points. Teams are ranked firstly based on their accumulated points and secondly by their accumulated score difference.

$Score\_Diff_{ijklt}$ is used as the dependent variable for team performance, measuring the goal difference between a team and its opponent per game.[8] I apply a basic approach that includes club fixed effects (γ_i) and manager fixed effects (λ_j). Following Mühlheusser et al. (2016), Peeters et al. (2015), and Santos (2014), the model consists of time-varying control variables (βX_{ikt}). Every team plays one game at home and one away against the same opponent within a season. Across different sports, it has been documented that playing at home provides an advantage (Peeters et al., 2015; Szymanski, 2015). Hence, home advantage is taken into account as a control variable. This advantage could be partly explained by the larger fan support at the home stadium, but also due to less exhaustion from the journey to the stadium (Pollard and Pollard, 2005). To control for the impact of fans, the attendance per game is used as a control variable as well. According to Szymanski (2015), a manager might be more successful with a higher valued team, which clearly does not reflect the managerial impact on team performance. I include the time-variant variable *team value* for both teams as they might have a crucial influence on team performance.[9] In addition, I control for fixed effects of the opponent club (δ_k) and opponent manager (θ_v) as both might influence the managerial impact on team performance. Lastly, ε_{ijkvt} represents the error term.

Clearly, λ_j and γ_i can only be observed together as club i can only be identified with manager j. This means that club i can just be observed with manager j and vice versa. In other words, it is impossible to unbundle fixed effects of clubs and managers, when clubs are not connected by moving managers. Therefore, for those clubs including their non-moving managers, fixed effects cannot be disentangled. On the other hand, manager fixed effects can be estimated separately for clubs observed with managers that moved between the observed clubs at least ones. As such, fixed effects are estimated following the seminal article of Abowd et al. (1999) in order to identify the unbundled impact of managers on team performance. In my dataset, clubs are connected via so-

[8] Measuring performance of a football team is generally reflected by the amount of points achieved within a season. Nonetheless, a team can receive zero, one or three points per game, showing that this performance measure is discontinuous. Another performance measure, and certainly the more important one for seasonal success, is a club's league position. However, besides the end position the ranking per match day tells us little whether a team performed better. Therefore, I follow the approach of Peeters et al. (2017) by using the goal difference between two clubs per game as a continuous variable that directly reflects, whether a team performed well.

[9] I observed total team values per season for each Bundesliga club from the platform transfermarkt.de. Due to data availability and as other platforms (e.g., kicker.de, sport1.de) and serious newspapers (e.g., Frankfurter Allgemeine Zeitung) commonly refer to those values in their sports sections, I use team values as an indicator for a club's financial strength.

called ‘movers’ into one network. First, I estimate which clubs are connected to the biggest network by using the approach of Cornelissen (2008). Then, I drop those observations that are not part of the largest network. Table III in appendix B presents the eliminated teams and their managers. As data was observed on a match day basis, both clubs need to be part of this connected network (Peeters et al., 2017). Therefore, games in the dataset are doubled, taking into account the perspective of each team to avoid linear restrictions on the dummies for managers and clubs. Table 1 provides the output table that clusters observations into groups, based on manager mobility across the clubs.

Table 1: Stata Output of ‘felsdvreg’ - Groups of Clubs connected by Manager Mobility

Group	Manager matches	Manager	Movers	Clubs
0	306	9	0	6
1	6,290	103	33	25
2	136	3	1	2
Total	6,732	115	34	33

Notes: Table 1 shows the Stata output of the Stata command ‘felsdvreg’, following the two way high-dimensional effects model of Cornelissen (2008).

As Dawson et al. (2000) analyzed the appropriateness of alternative models and Bertrand and Schoar (2003) and Peeters et al. (2015) provide arguments for using the fixed effects (FE) approach of Cornelissen (2008), this method provides several advantages compared to other models such as ordinary least squares (OLS). First, FE models allow for time-fixed unobserved heterogeneity which is likely to be correlated with the observations. Furthermore, a two way high-dimensional FE model makes it possible to include more than one fixed effect. Even though this approach helps to achieve better estimates for the time-varying betas, the main objective are the fixed effects of variables itself. Following Mühlheusser et al. (2016), I also drop observations for those matches where the team was coached by an interim manager. The adjusted sample consists of 5,873 games coached by 97 managers that are connected by 33 movers.

4.2 Identification of Manager Characteristics and Tactical Impact

In the second part, I analyze a set of hypotheses that concern a manager's characteristics and tactical and strategic decisions. I examine a second hypothesis to see if a manager's impact on team performance can be assigned to specific characteristics.

H_2: The impact of Bundesliga managers on the team performance of Bundesliga clubs can be assigned to specific manager characteristics.

Following Mühlheusser et al. (2016) and Peeters et al. (2015), I estimate regression models with variables to proxy for manager characteristics. They are covered by their experience in years, number of clubs managed, whether a manager was a former professional player and which position he played. Model (2) defines the relationship between managerial characteristics and team performance.

$$Score\_Diff_{ijkvt} = \sum_{j=1}^{k} \alpha_j + \beta X_{ikt} + \gamma_i + \theta_k + \vartheta_v + \mu_{ijkvt} \qquad (2)$$

With $\sum_{j=1}^{k} \alpha_j$, I measure the relationship of a manager j*'s* characteristics with the dependent variable for a team i*'s* performance. I insert the same control variables for team *i* and the opponent team *k* in match *t* from the equation (1), expressed with βX_{ikt}. Moreover, I control for club fixed effects (γ_i), and fixed effects of the opponent club *k* (θ_k) and manager *v* (ϑ_v). The error term is represented by μ_{ijkvt}.

For the remaining two hypotheses, I examine managers' tactical and strategic choices, which cover the organization and planning part of the managerial task list. The third hypothesis regards the general effect of tactical decisions of managers.

H_3: The tactical decisions of Bundesliga managers have an impact on the team performance of Bundesliga clubs.

To operationalize the tactical decisions of managers, I use the team formation chosen by a manager for each game. At first, I create dummy variables for all 17 observed formations, which will be used as explanatory variables on score difference as the dependent variable. As such, I estimate regression models with fixed effects. Models include total team values for each team, fan attendance, and home advantage as control variables. Moreover, I control for opponent formation fixed effects. The regression equation is defined as

$$Score\_Diff_{ijkvt} = \sum_{j=1}^{k} \varphi_j + \beta X_{ikt} + \sigma_v + \mu_{ijkvt}, \quad (3)$$

with $\sum_{j=1}^{k} \varphi_j$ capturing the dummies for all 17 formations chosen by manager j, and βX_{ikt} including the above mentioned control variables for the (opponent) team *i* (*k*) in match *t*. σ_v represents opponent fixed effects of formations chosen by manager *v*. μ_{ijkvt} is used to express the error term. The objective is to estimate team *i*'s optimal formation against team *k* and to see whether specific formations are more relevant for team performance. However, 13 out of 17 formations were used with less than five percent in the dataset. This makes it difficult to derive a conclusion for those formations. Therefore, I adjust the main explanatory variables in equation (3) by taking the dummies of formations with more than five percent of observations into account. Fortunately, they cover 83 percent of the whole dataset (5,565 observations out of 6,732). The final four formations chosen by a manager are 4-4-2, 4-2-3-1, 4-3-3, and 4-1-4-1. All other 13 formations are grouped together as one dummy variable, which is then used as the comparable variable.

In the last step, I analyze whether managers' tactical decisions can be assigned to certain strategic orientations of the team. For example, a specific formation as a tactical proxy might relate to a more offensive strategy (e.g., more shots, corners) compared to other formations. Also, a formation could be accompanied by a more aggressive strategy (e.g., more fouls, cards). According to Mühlheusser et al. (2016) and Santos (2014), certain strategic orientations of a team are more successful compared to others. Hence, tactical choices might correlate with certain strategies.

H_4: A Bundesliga managers' tactical decisions can be assigned to specific team strategies of Bundesliga clubs.

I conduct regression models including fixed effects to see which formations are significantly correlated with specific variables that represent a team's strategy. Following Mühlheusser et al. (2016) and Santos (2014), I proxy an offensive strategy with a team's amount of scores, shots, and corners. I additionally include the variable shots on target. Whether a team follows an aggressive strategy or not will be operationalized with fouls committed and the amount of yellow and red cards. Two baseline specifications define the empirical models for the relationship between team formations and offensive (aggressive) oriented strategies.

$$Offensive_{ijkvt} = \sum_{j=1}^{k} \varphi_j + \beta X_{ikt} + \sigma_v + \mu_{ijkvt}, \qquad (4)$$

The dependent variable $Offensive_{ijkvt}$ captures the aforementioned variables that proxy offensive strategies. I create regression models for each variable. The main explanatory variables are dummies of the four most used formations ($\sum_{j=1}^{k} \varphi_j$) that are compared with all other formations. Also, I include control variables from the previous models (βX_{ikt}) and control for opponent formation fixed effects (σ_v). The error term is represented by μ_{ijkvt}. Next, I consider the empirical model (5) below.

$$Aggressive_{ijkvt} = \sum_{j=1}^{k} \varphi_j + \beta X_{ikt} + \sigma_v + \mu_{ijt}, \qquad (5)$$

The model defines the relationship between aggressive oriented strategic variables ($Aggressive_{ijkvt}$) and variables used in equation (4).

In addition, I apply a Multinomial Logistic Regression (MLR) analysis. In order to explain the impact of a team's strategic orientation on the likelihood that a certain formation is chosen, I consider the empirical model below. More importantly, the analysis is used to provide results for the relationship between tactical decisions and control variables such as (opponent) team values. Assuming that the rest of formations is used as a reference category, the regression equation is defined as

$$\frac{P(Y_i=m)}{P(Y_i=1)} = \alpha Offensive_{ikt} + \beta Aggressive_{ikt} + \gamma X_{ikt} + \sigma_v + \mu_i, \qquad (6)$$

where $\frac{P(Y_i=m)}{P(Y_i=1)}$ is the probability that formation *m* of team *i* is more (or less) likely to be chosen against team k in match *t*. This probability is explained by $Offensive_{ikt}$ and $Aggressive_{ikt}$, including the aforementioned variables as proxies for a team's strategic orientation. Furthermore, the model includes control variables (γX_{ikt}) that were used for equation (4) and (5) as well. With σ_v, I control for opponent formation fixed effects. μ_i represents the error term. To conduct this method, the dependent variable is independent among the given choices, and errors are identically and independently distributed (Menard, 2002).

5 Main Empirical Results

5.1 Analyzing the (Joint) Managerial Impact on Team Performance

Table 2 shows summary statistics and correlations of the variables used for the first hypothesis. Descriptive statistics are shown in column two to five, followed by the correlation matrix.

Table 2: Summary Statistics – Variables of First Hypothesis

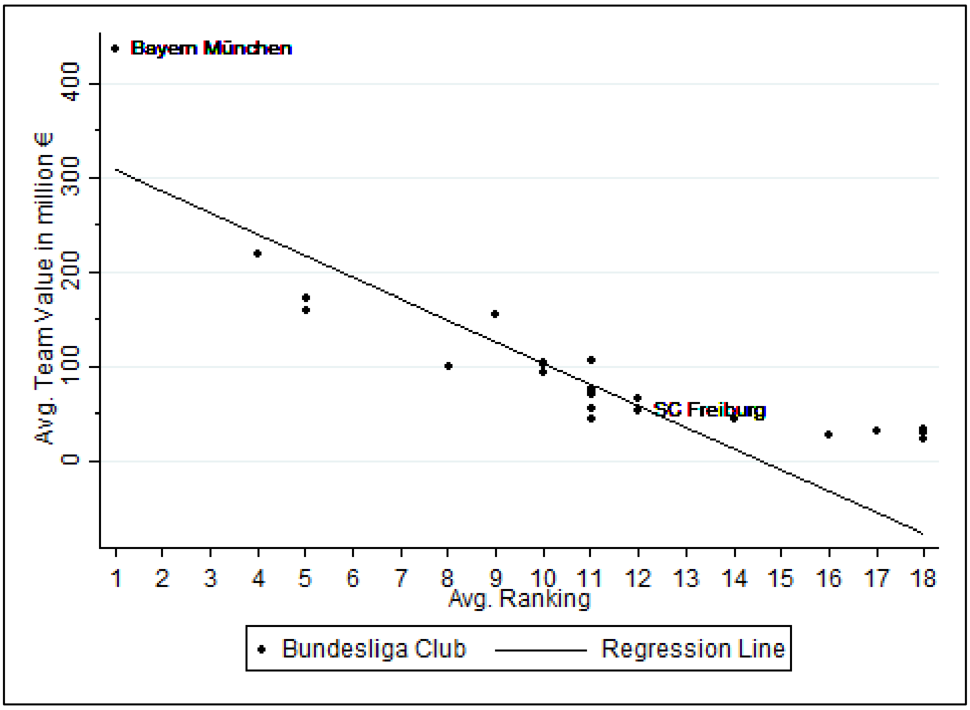
Variable	Mean	Std. dev.	Min.	Max.	1	2	3	4	5
Score difference	0.38	1.876	-7	8	1.00				
Attendance	43,981	16,836	14,401	81,360	0.00	1.00			
Home advantage	-	-	-	-	0.20	0.00	1.00		
Team value in €m	121.24	110.57	19.8	779.0	0.26	0.28	0.00	1.00	
Opp. Team value in €m	121.27	110.56	19.8	779.0	-0.25	0.28	0.00	0.01	1.00

Notes: Table 2 provides descriptive statistics of the variables used for the first hypothesis. For explanatory purposes, the non-doubled dataset is used for descriptive statistics, containing 2,937 observations. Statistics were estimated after the dataset was adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, three observations were deleted due to the non-interim condition. Note that summary statistics for the variable *Home advantage* are excluded as the non-doubled variable only reflects home teams. In addition, columns '1' to '5' show the correlations between all variables for the first hypothesis. Correlations are estimated with the full dataset, which is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. In total, the full dataset contains 5,873 observations.

On average, the score difference is 0.38 for all observed matches regarding the home team perspective. 43,981 fans attended on average at a Bundesliga match during the last 11 seasons. The average (opponent) team value is €121 million across all seasons. Interestingly, Bundesliga clubs seem to be quite heterogeneous in terms of their team values. For instance, the lowest observed seasonal team value of a Bundesliga club is €19.8 million (Darmstadt 98). On the other hand, the highest value is far above average with €779 million (FC Bayern München). Figure 1 provides an overview of the relation between the average ranking as a proxy for team success and the average team value of Bundesliga clubs.[10]

[10] To provide a clearer picture of performance, a team's average league position for all 11 seasons is used. Using the average of the variable score difference for all 11 seasons would not provide a better output, as results would tend toward the mean.

Figure 1: Relation between Average Team Values and Average Club Ranking from Season 2007/2008 to 2017/2018



Notes: Figure 1 shows the relation between the average ranking of a Bundesliga club and its average seasonal team value in million € from season 2007/2008 to 2017/2018. In addition, fitted values are included as a simple regression line. Data for team values and team rankings originate from transfermarkt.de.

Figure 1 shows that clubs with a lower average team value over the last 11 seasons also have a lower average position at the end of the season. For example, Bayern München has constantly the highest team value in all 11 seasons and is also ranked first on average. On the other hand, SC Freiburg (as a consistent first league club in the past 11 seasons) has one of the lowest values over time, which is in line with a lower average ranking (position 12). In addition, clubs below the regression line might be able to outperform their expected end position due to other influential factors.

Table 3 presents a series of regression results.[11] An F-test is conducted in order to see whether manager fixed effects on team performance are jointly significant. In terms of a model's goodness of fit, the R^2 and adjusted R^2 are taken into account.

[11] I conducted histograms to check whether the dependent variable score difference and manager fixed effects as a main explanatory variable are normal distributed. Figure I and figure II in the appendix A provide the distribution of observations. Both variables are normal distributed. In contrast, the control variables for fan attendance and (opponent) total team value are skewed. To overcome this issue, I use the natural logarithms for both variables.

Table 3: Regression Results – First Hypothesis

Team performance	(1) Club FE incl. opp. FE	(2) Manager FE incl. opp. FE	(3) All FE
Ln attendance per 10,000 visitors	0.011	0.065	-0.001
	(0.083)	(0.077)	(0.082)
Home advantage	0.767***	0.769***	0.768***
	(0.044)	(0.044)	(0.044)
Ln total team value	0.297***	0.486***	0.087
	(0.079)	(0.060)	(0.108)
Ln opp. total team value	0.042	-0.119	-0.086
	(0.102)	(0.106)	(0.108)
Opponent club FE	YES	YES	YES
Opponent manager FE	YES	YES	YES
Club FE	YES	NO	YES
F-test	8.30***	-	7.99***
Manager FE	NO	YES	YES
F-test	-	2.91***	2.17***
Observations	5,873	5,873	5,873
R^2	0.159	0.170	0.179
Adj. R^2	0.136	0.137	0.143

Notes: Table 3 summarizes three regression models, including either club fixed effects, manager fixed effects or both. Opponent club and manager fixed effects are used as control variables. The dataset is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The reported F-test results from the models that include manager fixed effects indicate that the estimated fixed effects have a significant impact on team performance. As such, I accept the first hypothesis that claims that managers of Bundesliga clubs have an impact on team performance. This is consistent with Mühlheusser et al. (2016). Moreover, my results are comparable with those of Peeters et al. (2015), who estimated the impact of Major League Baseball head-coaches and general managers on team production. Using the respective interim managers as a zero category, they also show that managers (head-coaches) have a significant impact on performance.

Estimates on home advantage are significantly positive, which is in line with the studies of Mühlheusser et al. (2016), Peeters et al. (2015), Pollard and Pollard (2005), and Szymanski (2015). Ceteris paribus, a team increases its score difference by 0.77 goals on average when playing at home. Further, the control variables fan attendance and opponent team value are insignificant for all three models.

Coefficients for the variable total team value are significant and positive as long as both club and manager fixed effects are not included. This seems to be valid as team values are attached to Bundesliga clubs and mainly observed with one manager for each season in the dataset. This might also explain the insignificance of opponent team values because opponent club and manager fixed effects are included in all three models. Following Mühlheusser et al. (2016) and Peeters et al. (2015), results for manager fixed effects might be more accurate and stable when including an indicator for a club's financial strength.

In table IV in appendix B, I test the robustness of the estimated results by excluding control variables while including fixed effects. All observed coefficients are in line with the results from table 3, which indicates that the assessed regression results seem to be robust. Regarding the correlation matrix from table 2, no variable is highly intercorrelated. In other words, no variable can be linearly predicted from other included variables and hence, the regression models might not issue multicollinearity.

Results for manager fixed effects only regard for joint fixed effects. Hence, it does not give insights for individual managers. Still, they differ in their abilities (Bertrand and Schoar, 2003). To provide an overview of individual managers, table 4 illustrates the top ten and bottom ten in terms of their fixed effects on team performance as well as their average points won.

Table 4: Top 10 and Bottom 10 Ranking of Manager Fixed Effects versus Average Points Won

Rank	Manager	Obs.	Coeff.	Rank	Manager	Obs.	Avg. points
1	André Schubert	41	2.034	1	Pep Guardiola	98	2.520
2	Julian Nagelsmann	75	2.023	2	Carlo Ancelotti	36	2.375
3	Christian Gross	26	2.001	3	Ottmar Hitzfeld	26	2.235
4	Lorenz Günther Köstner	24	1.926	4	Jupp Heynckes	161	2.226
5	Lucien Favre	211	1.887	5	Sascha Lewandowski	44	2.044
6	Mike Büskens	34	1.819	6	Louis van Gaal	61	1.937
7	Domenico Tedesco	32	1.802	7	Jürgen Klopp	228	1.912
8	Pál Dárdai	109	1.778	8	Jürgen Klinsmann	26	1.862
9	Huub Stevens	109	1.691	9	Domenico Tedesco	32	1.853
10	Jens Keller	64	1.677	10	Martin Jol	30	1.794
68	Zvonimir Soldo	42	0.437	68	Stale Solbakken	28	0.967
69	Robin Dutt	134	0.405	69	Hans Meyer	35	0.956
70	Louis van Gaal	61	0.311	70	Thomas Schneider	19	0.952
71	Christoph Daum	37	0.128	71	Stefan Ruthenbeck	19	0.950
72	Stefan Ruthenbeck	19	-0.008	72	Torsten Frings	16	0.944
73	Frank Schaefer	25	-0.079	73	Michael Frontzeck	119	0.938
74	Jürgen Klinsmann	26	-0.080	74	Gertjan Verbeek	21	0.909
75	Marcus Sorg	16	-0.167	75	Norbert Meier	45	0.809
76	Stale Solbakken	28	-0.197	76	Marcus Sorg	16	0.765
77	Thomas Doll	26	-0.515	77	Michael Oenning	31	0.677

Notes: Table 4 presents a comparison of the ranking of top 10 and bottom 10 manager fixed effects and average points won, accounting for control variables (home advantage, fan attendance, (opponent) total team value). Descriptive statistics were estimated after the dataset was adjusted for managers that satisfy the 'felsdvreg' and non-interim condition. Referring to Mühlheusser et al. (2016), only managers that coached at least one half season (more than 16 matches) were taken into account.

Regarding the left part of the table, there is a clear difference in manager fixed effects between the top and bottom managers. Interestingly, the top ten consists of managers from clubs that are on average ranked in the middle or second half of the league table. For instance, André Schubert managed the team of Borussia Mönchengladbach, which is on average ranked on position eight. This is in line with figure 1 that shows that middle clubs are ranked higher than the regression line would expect in terms of their average team values. Hence, their managers might be a factor for this outperformance.

On the right side, managers who coached a team of the four highest valued Bundesliga clubs (Bayern München, Borussia Dortmund, FC Schalke 04, and Bayer Leverkusen) are observed with the highest average points won. Nonetheless, the managers Louis van Gaal and Jürgen Klinsmann show that Bayern München’s success might not be based on their managerial impact. They both are part of the bottom ten managers in terms of fixed effects on team performance. On the other hand, the manager Julian Nagelsmann who coached the team of TSG Hoffenheim has a larger impact on team performance compared to other managers. Nagelsmann has one of the highest observed fixed effects on team performance and is also ranked high on position 12 in terms of average points won (1.71 points). Taking Hoffenheim’s average ranking on position ten into account, he clearly has an impact as Hoffenheim ranked on position three and four under his management. Mühlheusser et al. (2016) observed similar results for Bundesliga managers.

5.2 Analyzing Impacts of Characteristics and Behavior on Team Performance

5.2.1 The Impact of Manager Characteristics on Team Performance

In this section I investigate the connection between individual managerial characteristics and team performance. Table 5 provides descriptive statistics of managers' backgrounds as ratios and their coaching experiences in years.

Table 5: Managers' Background as Professional Players and Coaching Experience

Manager Type	Total	Former professional	National (GER)	Offensive	Avg. experience in years
All managers	97	0.861	0.701	0.690	16.7
Only movers	33	0.848	0.788	0.643	18.9

Notes: Table 5 provides descriptive statistics of managers that satisfy the 'felsdvreg' and non-interim conditions. Former Professional, National (GER), and Offensive are given as ratios of the total amount of managers (see second column). Managers that were accounted to be movers are separately listed.

The average experience of the considered managers is 16.7 years. The average manager of the adjusted dataset coached 5.5 clubs. Nearly nine out of ten were former professional football players, from whom the majority played in an offensive position, namely midfield or forward. Interestingly, the majority of managers are German, which is in line with Frick and Simmons' (2008) findings. According to them, German clubs in general hire only managers with a diploma received from Cologne Sports University.[12] Managers that are also movers are more likely to be German and have a longer experience compared to non-movers. Table 6 shows a set of regression results with manager characteristics as main explanatory variables. I further control for club and opponent fixed effects.

[12] Due to this requirement, which is also an entry barrier for foreign managers, German managers that got dismissed have a high chance to get rehired by a German club (Frick and Simmons, 2008). Furthermore, German clubs are mainly unwilling to hire a non-German speaking manager. However, due to the affiliation of the Bundesliga to the Union of European Football Associations (UEFA), manager with a Pro-license, which is comparable to the German license 'Fußballlehrer', are allowed to manage the first team of a Bundesliga club as well (DFB, 2018).

Table 6: Regression Results – Second Hypothesis

Team performance	Model 1	Model 2	Model 3	Model 4
Characteristics:				
Experience in years	-0.001	0.008	0.008	0.008
	(0.004)	(0.005)	(0.005)	(0.005)
No. clubs managed		-0.033**	-0.033**	-0.035**
		(0.014)	(0.014)	(0.015)
Professional player			0.048	-0.011
			(0.078)	(0.119)
Player position				0.034
				(0.051)
Inputs:				
Ln attendance per 10,000 visitors	0.011	0.008	0.009	0.009
	(0.083)	(0.083)	(0.083)	(0.083)
Home advantage	0.767***	0.767***	0.767***	0.767***
	(0.044)	(0.044)	(0.044)	(0.044)
Ln total team value	0.297***	0.271***	0.269***	0.270***
	(0.079)	(0.080)	(0.080)	(0.080)
Ln opp. total team value	0.041	0.022	0.023	0.019
	(0.103)	(0.103)	(0.103)	(0.103)
Club FE	YES	YES	YES	YES
Opponent club FE	YES	YES	YES	YES
Opponent manager FE	YES	YES	YES	YES
Observations	5,873	5,873	5,873	5,873
R^2	0.159	0.160	0.160	0.160
Adj. R^2	0.136	0.136	0.136	0.136

Notes: Table 6 presents four regression models. All models control for club fixed effects and opponent fixed effects. Score difference is used to proxy team performance. The dataset is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. Characteristics of managers are used as main explanatory variables. Inputs are used as control variables. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 6 shows that results for the amount of clubs managed are consistently significant and negative for models 2 to 4. According to this, I can accept the second hypothesis. The managerial impact on team performance can be assigned to specific characteristics.

Note that I find no significant impact whether a manager was a former professional player. Even though this is contrary to Mühlheusser et al. (2016), their analysis did not take fixed effects into account. Coefficients for the control variables home advantage and total team value are both positive and significant at a one percent level. On the other hand, coefficients for opponent team values and fan attendance are insignificant in all four models. This is consistent with my findings in table 3. Moreover, after adding more characteristic variables to the regression, coefficients remain constant.

5.2.2 The Impact of Tactical Choices on Team Performance

In this part, I analyze how managers' tactical decisions affect team performance. Table 7 provides descriptive statistics for each of the 17 observed formations that proxy those tactical choices.[13]

Table 7: Summary Statistics – Starting Formations of Bundesliga Teams

Formation	Obs.	Mean	Std. dev.	Avg. points	Avg. score diff.	Avg. team value in €m	Avg. home ratio
4-4-2	2318	0.344	0.475	1.40	0.00	99.61	0.51
4-2-3-1	2282	0.339	0.473	1.42	0.08	126.48	0.51
3-5-2	152	0.023	0.149	1.29	-0.02	152.96	0.47
4-3-1-2	118	0.018	0.131	1.21	-0.10	92.29	0.43
4-5-1	247	0.037	0.188	1.24	-0.19	68.41	0.48
4-1-3-2	54	0.008	0.089	1.33	-0.06	113.29	0.44
4-3-3	490	0.073	0.260	1.48	0.22	156.12	0.52
4-4-1-1	122	0.018	0.133	1.00	-0.60	86.07	0.38
4-1-4-1	475	0.071	0.256	1.30	-0.16	126.60	0.49
3-4-3	45	0.007	0.081	1.56	0.31	212.75	0.51
3-4-2-1	102	0.015	0.122	1.32	0.03	180.57	0.47
3-1-4-2	60	0.009	0.094	1.62	0.32	148.27	0.65
4-3-2-1	100	0.015	0.121	1.39	0.09	106.43	0.44
5-4-1	97	0.014	0.119	0.85	-1.06	76.38	0.33
3-4-1-2	20	0.003	0.054	1.75	0.25	139.31	0.55
3-3-3-1	11	0.002	0.040	1.36	-0.27	106.69	0.36
5-3-2	39	0.006	0.076	0.92	-0.79	100.90	0.49

Notes: Table 7 summarizes descriptive statistics of starting formations used by Bundesliga teams during the observed time period. Data was derived from transfermarkt.de and weltfussball.de. For correctness and reliability, data was cross-checked with other sources, such as sport1.de, kicker.de, and bundesliga.de.

The most commonly used formation is 4-4-2[14], followed by 4-2-3-1. The least chosen formation is 3-3-3-1, mainly applied by Hans Meyer with Borussia Mönchengladbach in season 2008/2009. Variations regarding the last four columns seem to be low across formations. Even though some of them might accompany with higher valued teams (e.g., formation 3-4-3), observations for those formations are small. As

[13] A formation consists of the ten field players, who are in general assigned to either a defending position, midfield position, or forward position (Wilson, 2014). For example, the commonly used 4-4-2 formation implies four defenders, four midfield players, and two forwards. However, some formations contain more than three digits. This depends on two-dimensional coordinates on the football pitch. Players that have a similar distance to their goal line are summarized into one position. For example, the 4-2-3-1 formation contains of four defenders, two defensive midfield players, three offensive midfield players, and one forward.

[14] Due to different observations on transfermarkt.de and sport1.de of the specific kind of 4-4-2 formation (e.g., there exist an offensive, defensive and Route formation), I only use the term 4-4-2 for all kinds of this specific formation.

such, I use a dummy *Rest* for all formations with less than five percent of observations as the reference category. Table 8 provides regression results of two estimated models.

Table 8: Regression Results – Third Hypothesis

Team performance	Model 1	Model 2
Formation:		
4-4-2	0.174**	0.010
	(0.072)	(0.071)
4-2-3-1	0.188***	0.042
	(0.072)	(0.071)
4-3-3	0.241**	0.133
	(0.108)	(0.104)
4-1-4-1	0.129	0.055
	(0.105)	(0.102)
Rest	omitted	omitted
Inputs:		
Ln attendance per 10,000 visitors	-0.348***	-0.007
	(0.062)	(0.063)
Home advantage	0.745***	0.758***
	(0.047)	(0.046)
Ln total team value	0.757***	0.706***
	(0.037)	(0.036)
Ln opponent total team value		-0.704***
		(0.036)
Opponent formation FE	YES	YES
Observations	5,873	5,873
R^2	0.104	0.158
Adj. R^2	0.101	0.155

Notes: Table 8 summarizes two regression models, including opponent formation fixed effects. Model 2 further includes opponent team values. Score difference is used to proxy team performance. Formations are used as main explanatory variables. Inputs are included as control variables. The dataset is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Except 4-1-4-1, using one of the other formations has a significant and positive effect on team performance compared to the rest of formations (model 1). From this, I conclude that the tactical choice of the manager has an impact on team performance. Hence, I accept the third hypothesis.

Model 1 further shows a significant and negative impact of fan attendance on team performance. This is in line with the findings of Garicano et al. (2005), who found that a higher fan attendance implies also more pressure on referees but also on team performance, which might then decline. When controlling for opponent team values in model 2, the coefficient for fan attendance becomes insignificant and less negative. This suggests that a better opponent club and its manager attracts a larger attendance and negatively influences team performance. Moreover, the coefficient for team values is highly significant and positive in both models. This is in line with Kuper and Szymanski (2014) and Szymanski (2014), who highlight that a club's financial strength is a main factor for success.

As model 2 shows, control variables are consistent with those from previous regression models and in line with the aforementioned literature. Interestingly, coefficients for the most used formations become insignificant when adding opponent total team values in model 2. As such, opponent team values take over the significant effect on team performance. The higher the opposite team value is, the worse is the team performance on average.

5.2.3 Strategies behind Managerial Tactics

Following Mühlheusser et al. (2016) and Santos (2014), it seems that tactical choices can be assigned to specific strategic orientations. Table 9 shows summary statistics of the main explanatory variables that proxy strategies used for the fourth hypothesis.[15]

Table 9: Summary Statistics – Fourth Hypothesis

Strategic Variable	Description	Mean	Std. dev.	Min	Max
Offensive/Defensive:					
Score	Amount of goals per game per team	1.44	1.29	0	9
Shots	Amount of shots per team	13.01	5.10	0	36
Tarshots	Amount of shot on target per team	4.71	2.56	0	15
Corners	Amount of corners per team	4.92	2.78	0	20
Aggressive/Passive:					
Fouls	Amount of fouls committed per team	15.63	4.70	1	34
Ycard	Amount of yellow cards per team	1.78	1.24	0	7
Rcard	Amount of red cards per team	0.09	0.30	0	3

Notes: Table 9 presents descriptive statistics of the variables used for the fourth hypothesis. The dataset is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. In total, the dataset contains of 5,873 observations.

On average, a team scores 1.44 goals per match and shoots 13.01 times from which 4.71 are on target. The average team has nearly five corners per match. In terms of fair play, a team commits on average 15.63 fouls and receives 1.78 yellow and 0.09 red cards.

[15] For a better readability of table 9, the correlation matrix of the used variables in hypothesis four are presented in Table V in the appendix B.

Table 10 provides regression results for the fourth hypothesis. Formations observed with less than five percent within the dataset are used as the reference category (Rest). In addition, opponent formation fixed effects are included as a control variable.

Table 10: Regression Results – Fourth Hypothesis

Strategy	Offensive/Defensive				Aggressive/Passive		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	Score	Shots	Shots on target	Corners	Fouls comm.	Yellow cards	Red cards
Formation:							
4-4-2	0.017	0.045	0.047	0.092	0.387**	-0.058	0.024**
	(0.049)	(0.184)	(0.096)	(0.105)	(0.181)	(0.049)	(0.012)
4-2-3-1	0.010	-0.044	0.015	0.096	0.089	-0.092*	0.029**
	(0.049)	(0.184)	(0.095)	(0.105)	(0.181)	(0.049)	(0.012)
4-3-3	0.011	0.047	-0.190	0.219	0.378	-0.168**	0.012
	(0.073)	(0.272)	(0.141)	(0.155)	(0.268)	(0.073)	(0.018)
4-1-4-1	-0.020	0.444*	0.122	0.422***	-0.284	-0.194***	-0.000
	(0.071)	(0.266)	(0.138)	(0.152)	(0.262)	(0.071)	(0.017)
Rest	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Inputs:							
Ln attendance	0.020	-0.006	0.053	0.148	-0.449***	-0.088**	-0.000
per 10k visit.	(0.044)	(0.163)	(0.085)	(0.093)	(0.161)	(0.044)	(0.011)
Home	0.377***	2.668***	1.000***	1.201***	-1.019***	-0.319***	-0.022***
advantage	(0.032)	(0.120)	(0.062)	(0.068)	(0.118)	(0.032)	(0.008)
Ln total	0.436***	1.974***	1.031***	0.671***	-1.148***	-0.185***	-0.010
team value	(0.025)	(0.095)	(0.049)	(0.054)	(0.093)	(0.025)	(0.006)
Ln opponent	-0.268***	-1.735***	-0.667***	-0.859***	-0.627***	0.016	-0.007
team value	(0.025)	(0.095)	(0.049)	(0.054)	(0.093)	(0.025)	(0.006)
Opp. form. FE	YES	YES	YES	YES	YES	YES	YES
Observations	5,873	5,873	5,873	5,873	5,873	5,873	5,873
R^2	0.091	0.185	0.138	0.114	0.056	0.031	0.003
Adj. R^2	0.087	0.181	0.134	0.111	0.052	0.027	-0.001

Notes: Table 10 shows the fixed effects regression models with the strategic variables as dependent variables. The rest of formations is used as the reference category for the four most used formations. Inputs are used as control variables and opponent formation fixed effects are included. The dataset is adjusted for managers that satisfy the ‘felsdvreg’ condition. Moreover, seven observations were deleted due to the non-interim condition. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Regarding columns (1) to (4) with offensive dependent variables, the choice for 4-1-4-1 on average increases the amount of shots and corners significantly, compared to the rest of formations. In other words, choosing this formation increases the offensiveness of a team. Coefficients for formation 4-4-2 show a significant and positive impact on fouls commited and the amount of red cards in columns (5) and (7). This means, that 4-4-2 increases the aggressive orientation of a team’s strategy. Formations 4-2-3-1, 4-3-3 and 4-1-4-1 however seem to follow a more passive strategy as coefficients for yellow cards are significantly negative in column (6). From these results, I can accept hypothesis four as tactical decisions of Bundesliga managers can be assigned to specific strategic orientations.

Regarding the control variables, a higher attendance significantly decreases the aggressive strategy of a team on average. Playing at home increases the offensiveness of a team significantly, but also decreases the aggressive orientation significantly. A manager might decide to play less physical to provide the fans of the club who attend a nicer match to follow. Nonetheless, this might be more in line with the findings of Garicano et al. (2005). They found that referees are more biased towards the home team due to social pressure of the crowd.

The higher the total team value, the more offensive and less aggressive a team plays. This is consistent with the results of Santos (2014). In addition, an opponent team that is higher valued decreases this offensiveness significantly. But it also makes the match less physical as a higher opponent team value significantly decreases the fouls committed of a team.

In addition, table 11 presents a multinomial logit regression with the remaining 13 formations (Rest) as a base category.

Table 11: Multinomial Logistic Regression Results – Fourth Hypothesis

Formation		4-4-2	4-2-3-1	4-3-3	4-1-4-1	Rest
Strategy:						
Offensive/Defensive						
Score		0.009	0.009	0.077	-0.032	
		(0.041)	(0.040)	(0.059)	(0.059)	
Shots		-0.003	-0.009	0.016	0.004	
		(0.013)	(0.013)	(0.018)	(0.018)	
Shots on target		0.008	0.007	-0.087**	0.005	
		(0.026)	(0.026)	(0.038)	(0.037)	
Corners		0.017	0.021	0.039	0.053**	
		(0.018)	(0.018)	(0.026)	(0.026)	
Aggressive/Passive						
Fouls committed		0.025***	0.010	0.035**	0.001	
		(0.010)	(0.010)	(0.014)	(0.014)	
Yellow cards		-0.070**	-0.076**	-0.159***	-0.126**	Base
		(0.035)	(0.035)	(0.053)	(0.052)	category
Red cards		0.293**	0.352**	0.152	0.039	
		(0.149)	(0.149)	(0.221)	(0.225)	
Inputs:						
Ln attendance		0.183*	0.229**	0.176	0.210	
per 10,000 visitors		(0.111)	(0.111)	(0.164)	(0.160)	
Home advantage		0.269***	0.318***	0.296**	0.089	
		(0.086)	(0.086)	(0.128)	(0.125)	
Ln total team value		-0.091	0.190***	0.459***	-0.449***	
		(0.068)	(0.067)	(0.098)	(0.101)	
Ln opponent		-0.544***	-0.485***	-0.319***	-0.212**	
total team value		(0.067)	(0.066)	(0.100)	(0.095)	
Opponent formation FE		YES	YES	YES	YES	
Observations	5,873					
Pseudo R^2	0.045					
Log likelihood	-7,907.58					

Notes: Table 11 summarizes the multinomial logistic regression models with the categorical variable formation as the dependent variable. Formations with observations lest than five percent of the dataset (Rest) are used as the base category. Inputs are used as control variables. All models include opponent formation fixed effects. The dataset is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Compared to table 10, the results in table 11 show similar outputs for the relationship between team formations and strategic orientation. Only for 4-3-3, the coefficient for shots on target becomes significant and negative. This means that relative to the base category, the formation 4-3-3 is on average more likely to follow a defensive strategy. Variables that proxy the aggressiveness (passiveness) of a formation are mainly significant. The team formations 4-4-2, 4-2-3-1 and 4-3-3 are more likely to be chosen when the team follows an aggressive strategy as coefficients for the variables fouls committed and red cards are significantly positive. In contrast, 4-1-4-1 is less likely to be chosen relative to the base category, because the coefficient for yellow cards is significantly negative. Hence, it seems that this formation follows a more passive strategy.

Except for 4-1-4-1, playing at home significantly increases the likelihood to use one of the other formations relative to the base category. For formations 4-4-2 and 4-2-3-1, this accounts for fan attendance as well as coefficients are significantly positive.

Overall, it seems that managers adapt their tactical decisions more to the observed input variables, meaning that they are strategically flexible. Especially (opponent) team values have a highly significant and positive (negative) impact. The higher the opponent's team value, the less likely is one of the four formations chosen, relative to the rest formations. On the other hand, the likelihood to choose the formations 4-2-3-1 or 4-3-3 significantly increases the higher the team value is. In contrast, this likelihood significantly decreases for formation 4-1-4-1. As such, I suggest that 4-1-4-1 seems to be a poor team strategy.

In comparison to table 4, eight of the top ten fixed effects managers prefer the formations 4-2-3-1 and 4-3-3. This means that they might not assign their tactical decision to an offensive (defensive) strategy since coefficients for those formations are insignificant. Still, it might not be clear which orientation is more successful relative to the base category. Formation 4-2-3-1 follows a more aggressive strategy and formation 4-3-3 a more passive one. Interestingly, the ten managers with the highest average points mainly prefer the formations 4-2-3-1, 4-3-3 and 4-4-2. This supports my suggestion that managers of higher valued teams tend to choose those specific formations over others.

In conclusion, I accept the fourth hypothesis. Both results from table 10 and table 11 show significances that strategies can be assigned to tactical choices of the manager.

6 Discussion and Concluding Remarks

This thesis presents new and updated insights on the topic of managerial impact on team performance. As such, I exploit a dataset on the labor market for managers that covers their characteristics and behavior (e.g., tactical decisions), firm input (e.g., team values) and firm output (e.g. match results). Following the main contributing literature, I focus on one professional sports, namely football. Moreover, I use data from the first German Bundesliga as it is available for the past 11 seasons. Therefore, I take the latest revealed league observations on team and manager performance into account. Due to the dataset's high quality, I am able to estimate a model that allows to compare managerial impact with personal characteristics and decision making. I empirically conduct a method to observe their effects following Abowd et al. (1999). I consider all instances of managers who got hired by a club and analyze their effects on the club's team performance. However, only those that are moving between clubs within the dataset and those who are comparable through the moving managers are taken into account. This allows me to avoid false interpretations of managerial effects and also to estimate individual fixed effects.

My results suggest that Bundesliga managers have a significant impact on the performance of Bundesliga teams. This effect can also be assigned to specific characteristics and tactical behavior. This is in contrast to Kuper and Szymanski's (2014) skepticism about this managerial impact. In detail, I show that managers of teams that are on average placed in the middle of the league table seem to have larger effects on team performance. This is consistent with Santos (2014). Regarding managers' tactical decisions, the most used formations in the dataset have a significant and positive impact on team performance compared to the less used ones. Taking my results for the fixed effects of top managers into account, they also prefer these most used formations. Nonetheless, managers are strategically flexible. They might adapt their strategic decisions to their home advantage, fan attendance, and especially team values. The higher the total value of a team, the more offensive but less aggressive it plays. Overall, my results show that (opponent) team values have a larger and more consistently significant effect on a team's success than the managerial impact through their characteristics and behavior. This is in line with Kuper and Szymanski (2014) and Szymanski (2015).

Of course, my empirical approach has potential limitations. The data used for my analysis might limit the generalizability. Football managers are too specific to compare them with their business counterparts. But, the aforementioned literature (e.g., Kahn, 2000) provides reasonable arguments that the sports industry can be used as an appropriate laboratory to research labor economic issues. Still, future researchers could expand the amount of data to provide an even more accurate picture of managerial impacts on team performance (e.g., including more seasons).

An important limitation of this thesis is the oversimplification of the tactical decision of managers. I have neglected several factors that might have a potential effect on the likelihood of a tactical change during a game because my data set did not contain relevant information. For example, a manager might change the team formation in terms of player suspensions, injuries, or the future transfer of a player. As such, Santos (2014) found differences between first-half and second-half strategies. Due to the availability of data, I used only the released formations at the beginning of each match. A more detailed data set could provide further understanding of the importance of tactical decisions.

Even though a manager's role in a football club is complex, he has one main task – to increase the probability to win a match with a given budget and talent of players from this club. To do so, he has to train players well and spend money wisely. But more importantly, managers have to organize and choose the right talent, tactic and strategy used for each match to succeed. On top of that, they also have to adapt their strategic decisions based on their opponent team. In comparison, their business counterparts' success is dependent on a certain budget and their employees' productivity. They also have to decide how and with whom they can reach their company's objectives. Moreover, business managers have to consider competition and their competitors' strengths in terms of products but employees as well. According to my results, managers of football clubs, and also of other industries, have an impact on their team's performance. Eventually, their characteristics and tactical behavior might be key elements to analyze this impact. Still, the financial strength of a club seems to have the dominant effect on team success.

7 References

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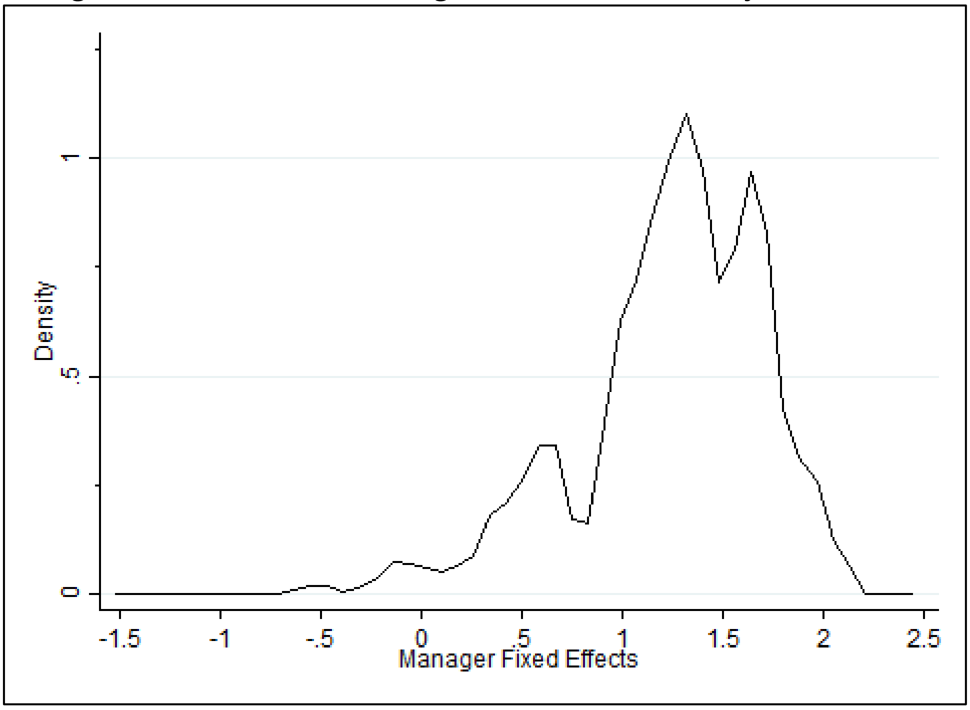
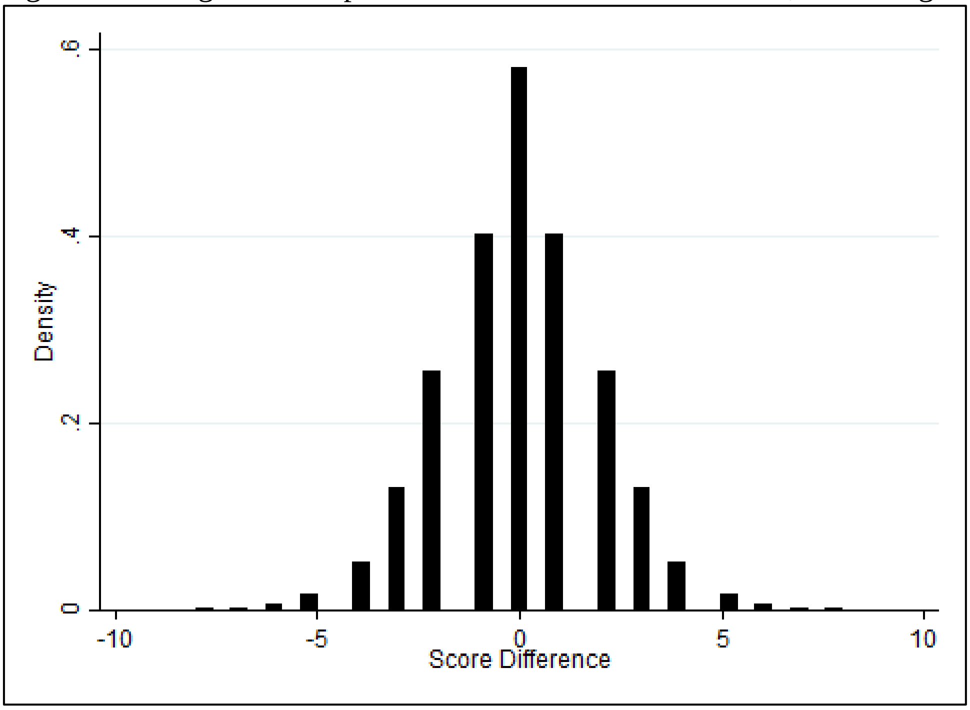
Appendix A

Figure I: Distribution of Manager Fixed Effects for Adjusted Dataset



Notes: Figure I depicts the distribution of manager fixed effects. Statistics were estimated after the dataset was adjusted for managers that satisfy the 'felsdvreg' and non-interim conditions. The level of observation is based on match day data.

Figure II: Histogram of Dependent Variable Score Difference, all Managers



Notes: Figure II depicts the distribution of the dependent variable score difference in the first set of hypotheses. The level of observation is based on match day data.

Appendix B

Table I: Defintion of Main Variables

Variable	Definition	Variable	Definition
Match day related variables		**Manager related variables**	
season	year season ends	manager	manager name at matchday
competition	country in which game is played	manager_id	identifier of manager
division	division in which game is played	natio	nationality of manager
day	calendar day	natio_id	identifier of manager nationality
month	calendar month	interim	dummy equals 1 if manager was a caretaker, 0 otherwise
year	calendar year	exp_2018	total amount of years of experience from first manager position until 2018
score	amount of goals shot by club	exp	total amount of years of experience from first manager position until year of season
score_diff	score difference between team and opposite team	no_clubs	total amount of clubs managed by manager until 2018
points	points made by team	prof	dummy equals 1 if manager was a professional player, 0 otherwise
attendance	total attendance at match	mpos	position (defense, midfield, offense) of manager, if he was a professional player
stadium	stadium name of home team	mpos_id	identifier of position
stadium_id	identifier for home team stadium	license	highest 'degree'/license achieved by manager
st_cap	official maximum capacity for league games	license_id	identifier of license
st_util	ratio of matchday stadium utilization	pref_form	starting formation that was mostly used by manager in his career until 2018
home	dummy equals 1 if 'club' is formally home team, 0 otherwise	pref_form_id	identifier of preferred formation
match_id	identifier for each game, note that each game is twice in the data	**Tactical and strategic related variables**	
Club and league related variables		formation	match day starting formation of team
club	name of team	formation_id	identifier for formation of team
club_id	identifier for team name	shots	team shots per game
tvalue	total team value in season in million EUR	tarshots	team shots on target per gam
pos	final position of team at the end of the season	fouls	fouls committed per game per team
fouls	fouls committed per game per team	corners	amount of corners per game per team
		ycard	amount of yellow cards per game per team
		rcard	amount of red cards per game per team
		first_half	amount of goals shot by a team in the first halftime
		second_half	amount of goals shot by a team in the second halftime

Notes: Table I reports the definition of the main variables of the dataset. As data was derived on a match day basis, variables for the opponent team are included as well. Data was derived from transfermarkt.de and weltfussball.de. For correctness and reliability, data was cross-checked with other sources, such as sport1.de, kicker.de, and bundesliga.de.

Table II: Sample Information – Setting of Bundesliga

Rank	Implication of position	Home matches	Away matches	Cluster
1	UEFA Champions League	17	17	Top
2	UEFA Champions League	17	17	
3	UEFA Champions League	17	17	
4	UEFA Champions League	17	17	
5	UEFA Euro League	17	17	
6	UEFA Euro League Qualification	17	17	
7		17	17	In-between
8		17	17	
9		17	17	
10		17	17	
11		17	17	
12		17	17	
13		17	17	
14		17	17	Bottom
15		17	17	
16	2 Relegation Games against 3rd placed club of 2nd Bundesliga	17	17	
17	Relegation to 2nd Bundesliga	17	17	
18	Relegation to 2nd Bundesliga	17	17	

Notes: Table II gives an overview of the latest existing ranking of the first German Bundesliga, including the implication of the position and to which cluster it belongs. The team that wins the National Trophy 'DFB-Pokal' also receives a spot in the UEFA Euro League. If a club wins the 'DFB-Pokal' and is ranked among the first six clubs, then the club ranked on position 7 receives the spot for the Qualification for the UEFA Euro League and every higher ranked club gets the next better spot in an international tournament below the team that won the National trophy.

Table III: Teams Eliminated by 'felsdvreg' Condition

Team	No. of managers	No. of obs.	Managers	No. obs.
1. FC Kaiserslautern	2	68	Marco Kurz	60
			Krasimir Balakov	8
Eintracht Braunschweig	1	34	Torsten Lieberknecht	34
Energie Cottbus	3	68	Petrik Sander	6
			Heiko Weber	1
			Bojan Prasnikar	61
FC Ingolstadt	3	68	Ralph Hasenhüttl*	34
			Markus Kauczinski	10
			Maik Walpurgis	24
Hansa Rostock	1	34	Frank Pagelsdorf	34
Karlsruher SC	1	68	Edmund Becker	68
MSV Duisburg	1	34	Rudi Bommer	34
RB Leipzig	1	68	Ralph Hasenhüttl*	68
	∑13	∑442		∑442

Notes: Table III gives an overview of the eliminated clubs as they do not satisfy the felsdvreg condition through their managers. *Manager was observed with several teams, but managed teams do not satisfy the 'felsdvreg' condition.

Table IV: Robustness Check – First Hypothesis

Team performance	Model 1	Model 2	Model 3	Model 4
Home advantage	0.768***	0.768***	0.768***	0.768***
	(0.044)	(0.044)	(0.044)	(0.044)
Ln attendance per 10,000 visitors		-0.001	-0.002	-0.001
		(0.082)	(0.082)	(0.082)
Ln total team value			0.075	0.087
			(0.107)	(0.108)
Ln opponent total team value				-0.086
				(0.108)
Club FE	YES	YES	YES	YES
Manager FE	YES	YES	YES	YES
Opponent club FE	YES	YES	YES	YES
Opponent manager FE	YES	YES	YES	YES
Observations	5,873	5,873	5,873	5,873
R^2	0.179	0.179	0.179	0.180
Adj. R^2	0.143	0.143	0.143	0.143
F-test	2.31***	2.31***	2.16***	2.17***

Notes: Table IV summarizes four fixed effects regression models, including club and manager fixed effects and opponent fixed effects. Score difference is used to proxy team performance. The dataset is adjusted for managers that satisfy the 'felsdvreg' condition. Moreover, seven observations were deleted due to the non-interim condition. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table V: Correlation Matrix – Fourth Hypothesis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Score	1.000										
Shots	0.319	1.000									
Shots on target	0.579	0.687	1.000								
Corners	0.083	0.526	0.348	1.000							
Fouls committed	-0.082	-0.160	-0.126	-0.101	1.000						
Yellow cards	-0.112	-0.138	-0.126	-0.102	0.358	1.000					
Red cards	-0.081	-0.100	-0.095	-0.064	0.063	0.040	1.000				
Ln attendance	0.030	0.002	0.032	0.005	-0.113	-0.052	-0.012	1.000			
Home advantage	0.149	0.264	0.197	0.218	-0.111	-0.131	-0.036	-0.001	1.000		
Ln team value	0.229	0.250	0.264	0.160	-0.193	-0.110	-0.023	0.277	0.000	1.000	
Ln op. team val.	-0.142	-0.238	-0.180	-0.207	-0.112	0.006	-0.017	0.277	0.000	0.015	1.000

Notes: Table V provides the correlation matrix of the explanatory variables used for the fourth hypothesis.