The Contribution of Managers to Organizational Success: Evidence from German Soccer*

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Abstract

We study the impact of managers on the success of professional soccer teams using data from the German *Bundesliga*, where we are exploiting the high turnover of managers between teams to disentangle the managers' contributions. Teams employing a manager from the top of the ability distribution gain on average considerably more points than those employing a manager from the bottom. Moreover, estimated abilities have significant predictive power for future performance. Also, managers also affect teams' playing style. Finally, teams whose manager has been a former professional player perform worse on average compared to managers without a professional player career.

JEL-Codes: J44, J63

Keywords: Managerial Skills, Human Capital, Empirical, Fixed Effects, Professional Sports

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1 Introduction

It is widely believed that managers have a huge impact on the success of organizations. The ability of the person at the top affects an organization through a number of channels and should trickle down through the hierarchy and thus have a strong effect on organizational performance (Rosen, 1982). But how big are these effects? What difference does the quality of the single person at the top make for the overall performance of the organization? There is a recent empirical literature which aims at measuring the contribution of individual managers to the performance of their organization (see e.g., Bertrand and Schoar, 2003; Lazear et al., 2015; Graham et al., 2012) exploiting the variation which arises from the fact that, in the course of the careers, some managers are active in several organizations or functions which allows to disentangle their contribution from other factors. However, this is a difficult endeavor as CEOs, for instance, typically stay at the top of a specific firm for longer time periods and work as CEOs only for a very small number of different firms (very often only one) in their lifetime – which limits the scope to measure their contribution to organizational success.

In this paper, we consider this issue in the context of professional sports which, apart from being of interest in its own right, has further advantages for the question at hand: (i) team performance is publicly observable on a weekly basis and (ii) managers move very frequently between teams – much more frequently than managers in firms. And observing the same manager in different organizations thus using different sets of resources and working with different people is crucial to measure a manager's contribution to overall success. We use this information to estimate the impact of managers on team success, thereby also addressing the practical debate on this issue. For instance, in a popular book in the context of English soccer, Kuper and Szymanski (2009) are rather sceptical about the importance of managers, arguing that "[i]n a typical soccer talk, the importance of managers is vastly overestimated." (p. 123). The aim of our paper is to address this issue by disentangling econometrically the impact of individual managers from the overall strength of their respective team.

From a methodological point of view, we thereby follow the approach applied by

Abowd et al. (1999) (who use wages of employees working for different employers) and Bertrand and Schoar (2003) (who study CEOs working for different firms) and evaluate the impact of individual managers by estimating OLS regressions that include both team and manager fixed effects using data from the last 21 seasons of the *Bundesliga*, Germany's major soccer league. We then investigate the obtained manager fixed effects further and our results point to considerable heterogeneity:

For instance, teams employing a manager at the 80% ability percentile gain on average 0.30 points per game more than those employing a manager at the 20% ability percentile. This corresponds to a difference of 18% of the average number of points won per game. We also conduct a cross validation exercise by estimating manager fixed effects using the data only up to a certain season and then investigate whether these fixed effects are useful to predict future performance. We find that this indeed is the case: these measures of managerial ability have a substantial predictive power for future performance of the teams employing the respective manager. Furthermore, apart from team performance, we show that managers also have a significant effect on teams' playing style in terms of how offensively they play. We also find a negative correlation between the fixed effects for team performance and offensive style, supporting the view that successful managers are not necessarily the ones whose teams please crowds through their offensive play. Last, but not least, we investigate whether observable manager characteristics (in particular, whether they have been a former professional or even national team player and if so, on which position) also affects team performance. We find that if anything, the teams of managers who were former professionals perform worse on average than their less prominent counterparts.

Our paper contributes to the growing literature empirically analyzing the impact of managers on different economic measures, such as corporate behavior (Bertrand and Schoar, 2003), corporate tax avoidance (Dyreng et al., 2010), managerial compensation (Graham et al., 2012), or disclosure choices (Bamber et al., 2010). In a prominent study, Bertrand and Schoar (2003) assess the impact of managers on firm performance, analyzing to what extent manager fixed effects can explain the observed heterogeneity in corporate behavior. They use a manager-firm matched panel data set that comprises different CEOs in different firms and focus only on those firms that have employed at least one *mover* manager, i.e. a manager who can be observed in at least two firms. The results show that manager fixed effects are important determinants in explaining corporate behavior. More recently, Lazear et al. (2015) study data from a large call center where supervisors move between teams (and team composition varies over time) which allows to disentangle the effect of different supervisors on performance. To the best of our knowledge, our paper is the first to apply this idea to the professional sports sector. Moreover, all managers in our study operate in the same industry, and this industry attracts a huge amount of public attention. As a result, most of these managers are very well-known to the interested public, so that the estimated individual fixed effects are of interest in their own right. Furthermore, we show that the estimated effects are useful to predict performance later in the managers' careers. Hence, our results can be helpful in identifying "under-valued" managers.

A further strand of literature has followed a different methodological route in order to measure managerial quality in professional sports: In a first step, a (stochastic) efficiency frontier is estimated for each team, and then in a second step, the quality of a manager is assessed in terms of the team's proximity to this frontier during his term (see e.g., Carmichael and Thomas, 1995; Fizel and D'Itry, 1997; Dawson et al., 2000a,b; Dawson and Dobson, 2002; Kahane, 2005; Hofler and Payne, 2006). Frick and Simmons (2008) also use stochastic frontier analysis to show (also for the Bundesliga) that relative coach salaries have a significant impact on team efficiency.

The remainder of the paper is structured as follows: We first describe the data and the empirical framework in section 2. In section 3 we present our results with respect to the estimated manager fixed effects and the resulting heterogeneity of managers. Section 4 provides robustness checks along two dimensions: Firstly, we cross-validate our results by estimating first manager and team fixed effect s for a restricted sample, and then use these estimates to predict team performance for the remaining seasons in our data set (section 4.1). Secondly, we relax the assumption that all team-specific information is captured by a (time-invariant) team fixed effect, and consider (relative) team budgets as additional (time-variant) covariates (section 4.2). In section 5 we analyze the impact of managers on the offensive style of their teams. Section 6 investigates the impact of managers' background as professional players on team performance. Finally, section 7 discusses possible caveats of our framework and concludes.

2 Empirical Framework

2.1 Data

The German Bundesliga – one of the strongest and economically most viable soccer leagues in the world – consists of 18 teams, and in each season, each team plays twice against each other team (one home match for each team), resulting in two half-seasons with 17 match days each. In each match, a winning (losing) team is awarded 3 (0) points, a draw results in 1 point for each team, and teams are ranked according to their accumulated points.[1] Our data set contains all Bundesliga matches played in the 21 seasons from 1993/94 until 2013/14 (9 matches played on each of 714 match days leading to a total of 6426 matches).[2]

In our analysis, the unit of observation is the performance of a manager-team pair during a half-season (that is, match days 1 through 17 and 18 through 34, respectively). Therefore our dependent variable (*Points*) is the average number of points per game gained in the course of a half-season. Considering half-seasons has the advantage that a team faces each other team exactly once during that time, so that distortions due to different sets of opponents are reduced.

Throughout we refer to a *spell* as a non-interrupted relationship between a manager-

[1] When several teams have accumulated the same number of points, the goal difference is used as the tie-breaking rule. In the first two season covered 1993/94 and 1994/95 the Bundesliga still applied a "two-point rule" where the winner of a game was awarded two points instead of three. We converted the data from these two seasons to the three-point rule.

[2] A large part of the data was kindly provided by deltatre AG, but it is also publicly available, e.g., from the website www.weltfussball.de.

team pair.[3] To be considered in the subsequent analysis, we require that a spell must last for at least 17 consecutive matches in the Bundesliga, and throughout the paper we refer to this as the *Footprint* condition (F).[4] This condition excludes observations from managers who are responsible for a team only for a small number of games.[5] While such short-term managers might have an impact on the team's short-term performance, they are unlikely to "leave a footprint". Out of the 176 managers in our data set, 116 remain after condition F is applied. The 60 managers and corresponding 109 spells which do not satisfy condition F are excluded from the further analysis. On average these spells lasted for a mere 6 matches only (see Appendix B for more details).

Spells satisfying condition F often stretch over several half-seasons (thereby leading to multiple observations for our dependent variable), but the time interval of a spell does typically not divide evenly into half-seasons. The reason is that managers are frequently hired and dismissed within (half-) seasons.[6] In these cases, we consider the performance in all half-seasons of the spell, weighted with the number of matches in the respective half-season.[7]

[3]In a small number of cases, the same manager-team pair has multiple spells, that is, a team has hired the same manager again after several years, e.g., Ottmar Hitzfeld (Bayern Munich) or Felix Magath (Wolfsburg). We count each of such periods as separate spells.

[4]In a similar vein, Bertrand and Schoar (2003) require at least three joint years for a manager-firm pair to considered in the analysis. We have chosen 17 matches to limit the scope of distortions due to the strength of the opponent teams.

[5]For instance, there are interim coaches who are hired only for a small number of matches after a coach has been fired and before a permanent successor is found. In our sample, the average spell of such interim managers lasts for 2.35 matches only. But there are also some managers who are dismissed because of weak performance after being in office only for a small number of matches. Note that condition F gives rise to the possibility that teams feature an uneven number of half-season observations.

[6]Within-season dismissals are a very typical feature in European professional sports. On average, about 35-40% of the teams dismiss their manager within a given season at least once (see e.g. Muehlheusser et al., 2016; De Paola and Scoppa, 2012; Tena and Forrest, 2007; Audas et al., 2002). In the 21 seasons of our sample, we observe in total 192 such within-season dismissals.

[7]For example, when a manager is hired at match day 5, and fired after match day 30 of the same season, this spell satisfies condition F, and there are two observations for this manager-team pair (one for the first half-season encompassing match days 5 to 17 and one for the second with match days 18 to 30, respectively). To take into account that the spell covers none of these two half-seasons in full, the average points won in each half-season are weighed using analytic weights which are inversely proportional to the variance of an observation (Stata command *aweights*).

2.2 Identification of Manager Fixed Effects

We consider the following empirical model to explain the performance of team i under manager k in half season t

$$Points_{itk} = \gamma_i + \lambda_k + \alpha_t + \epsilon_{itk}, \quad (1)$$

where the dependent variable measures the average number of points per game won by team i during the half-season $t = 1, ...42$.

We start by applying a parsimonious approach and include only fixed effects for teams (γ_i), managers (λ_k), and half seasons (α_t) as explanatory variables. In a later robustness check, we also capture time-variant variation at the team level by including a proxy for their relative budgets in a given season (see section 4.2). However, our preferred approach does not include budgets as a team's budget will also depend on recent performance and thus will typically be influenced by the current manager.[8] Obviously, γ_i and λ_k cannot be identified separately when the respective teams and managers are only jointly observed (that is, team i is only observed with manager k, and manager k is only observed with team i) since both variables are perfectly collinear in this case. Hence, to identify the different fixed effects, (at least some) managers and teams must be observed with multiple partners (see e.g., Abowd et al., 1999; Bertrand and Schoar, 2003).

In the context of European professional soccer, the rate of manager turnover is quite high. One reason is the high frequency of within-season managerial change as discussed above, but replacing managers between seasons is also quite common.[9] As a result, our data contains a large number of managers which are observed with many different teams (up to seven), and many teams which are observed under many different managers (up to 13) which creates a large amount of variation in observed manager-team matches.

[8]For instance, the top 5 teams at the end of a season are allowed to participate in the UEFA competitions *Champions League* or *Europe League* in the following season, both of which are financially very attractive.

[9]In the 21 seasons in our data set, in addition to the 192 within-season dismissals, there are 59 cases of managerial change between seasons.

From a methodological point of view, this renders this industry particularly suitable for the identification of manager fixed effects.

Throughout, we distinguish between two types of managers: *movers* and *non-movers*. We refer to a manager as a (non-)mover when he is observed with at least two different (only one) team(s). Out of the 116 managers satisfying the footprint condition F, 44 (38%) managers are movers, while 72 (62%) are non-movers. As already explained, for all teams employing only non-mover managers, it is not possible to disentangle team and manager fixed effects, and therefore to identify a separate manager fixed effect. In contrast, for all teams observed with at least one mover manager, manager fixed effects can be estimated also for the non-mover managers. In line with Bertrand and Schoar (2003), we require that teams are observed with at least one mover, and refer to this as the mover-team (MT) condition. This condition is satisfied by 29 out of the 37 teams in our data set. The remaining 8 teams are excluded from the analysis.[10] The same is true for the 13 managers (none of them eliminated by condition F, all non-movers) who have been employed by these teams, leading to 13 excluded spells in addition to those already excluded due to condition F as explained above.[11] Our final data set covers 103 managers (44 movers, and 59 non-movers), 29 teams, 206 spells, and 764 observations for the dependent variable *Points*.

Table 1 gives an overview of all 103 managers in our final sample. As can be seen from the table, more than 80% of the 44 movers in our sample are either observed with two or three different teams. But we also observe managers who have worked for many more teams (up to seven as in the case of Felix Magath, for instance).

[10]Typically, these teams are small and enter the Bundesliga occasionally by promotion, and are relegated to the second division again after a small number of seasons. See Table 17 in Appendix C for more information on these teams and their managers.

[11]Note that we first apply condition F and then condition MT, thus excluding those (three) managers who did work for two different teams, but where one of the spells is eliminated by condition F, see Table 17 in Appendix C.

	Manager	No. of teams	No. of obs		Manager	No. of teams	No. of obs
1	Advocaat, Dick	1	2	53	Löw, Joachim	1	4
2	Augenthaler, Klaus	3	13	54	Magath, Felix	7	34
3	Babbel, Markus	3	6	55	Marwijk, Bert van	1	5
4	Berger, Jörg	3	11	56	Maslo, Uli	1	4
5	Bommer, Rudi	1	2	57	McClaren, Steve	1	2
6	Bongartz, Hannes	3	6	58	Meyer, Hans	3	13
7	Bonhof, Rainer	1	2	59	Middendorp, Ernst	1	6
8	Brehme, Andreas	1	5	60	Mos, Aad de	1	1
9	Daum, Christoph	3	13	61	Möhlmann, Benno	2	7
10	Demuth, Dietmar	1	2	62	Neubarth, Frank	1	2
11	Doll, Thomas	2	9	63	Neururer, Peter	3	13
12	Dutt, Robin	3	8	64	Oenning, Michael	1	1
13	Dörner, Hans-Jürgen	1	4	65	Olsen, Morten	1	5
14	Engels, Stephan	1	2	66	Pacult, Peter	1	4
15	Fach, Holger	2	4	67	Pagelsdorf, Frank	2	15
16	Favre, Lucien	2	12	68	Pezzaiuoli, Marco	1	1
17	Fink, Thorsten	1	5	69	Rangnick, Ralf	4	17
18	Finke, Volker	1	20	70	Rapolder, Uwe	2	3
19	Fringer, Rolf	1	2	71	Rausch, Friedel	2	8
20	Frontzeck, Michael	3	9	72	Rehhagel, Otto	3	13
21	Funkel, Friedhelm	6	27	73	Reimann, Willi	2	4
22	Gaal, Louis van	1	4	74	Ribbeck, Erich	2	5
23	Gerets, Eric	2	7	75	Rutten, Fred	1	2
24	Gerland, Hermann	1	2	76	Röber, Jürgen	3	16
25	Gisdol, Markus	1	3	77	Sammer, Matthias	2	10
26	Gross, Christian	1	3	78	Scala, Nevio	1	2
27	Guardiola, Pep	1	2	79	Schaaf, Thomas	1	29
28	Götz, Falko	2	9	80	Schaefer, Frank	1	2
29	Hecking, Dieter	3	16	81	Schlünz, Juri	1	3
30	Heesen, Thomas von	1	4	82	Schneider, Thomas	1	2
31	Herrlich, Heiko	1	2	83	Sidka, Wolfgang	1	3
32	Heynckes, Jupp	5	15	84	Skibbe, Michael	3	14
33	Hitzfeld, Ottmar	2	23	85	Slomka, Mirko	2	13
34	Hyypiä, Sami	1	2	86	Solbakken, Stale	1	2
35	Jara, Kurt	2	8	87	Soldo, Zvonimir	1	3
36	Jol, Martin	1	2	88	Sorg, Marcus	1	1
37	Keller, Jens	1	3	89	Stanislawski, Holger	2	4
38	Klinsmann, Jürgen	1	2	90	Stepanovic, Dragoslav	1	4
39	Klopp, Jürgen	2	18	91	Stevens, Huub	3	21
40	Koller, Marcel	2	9	92	Streich, Christian	1	5
41	Korkut, Tayfun	1	1	93	Toppmöller, Klaus	4	17
42	Krauss, Bernd	1	7	94	Trapattoni, Giovanni	2	8
43	Kurz, Marco	1	4	95	Tuchel, Thomas	1	10
44	Köppel, Horst	1	3	96	Veh, Armin	5	18
45	Körbel, Karl-Heinz	1	3	97	Verbeek, Gertjan	1	2
46	Köstner, Lorenz-Günther	2	6	98	Vogts, Berti	1	2
47	Labbadia, Bruno	3	11	99	Weinzierl, Markus	1	4
48	Latour, Hanspeter	1	1	100	Wiesinger, Michael	1	2
49	Lewandowski, Sascha	1	3	101	Wolf, Wolfgang	3	17
50	Lienen, Ewald	5	17	102	Zachhuber, Andreas	1	4
51	Lorant, Werner	1	15	103	Zumdick, Ralf	1	2
52	Luhukay, Jos	3	6		Total	∅2.62	$\sum$764

Only managers after application of conditions F and MT.
Unit of observation: Half-season
Time period: The 21 seasons from 1993/94 - 2013/14.

Table 1: The Bundesliga Managers in the Final Data Set

	Team	No. of managers	No. of movers	No. of non-movers	No. of obs
1	1860 Munich	3	1	2	22
2	Aachen	1	1	0	2
3	Augsburg	2	1	1	6
4	Bayern Munich	9	6	3	43
5	Bielefeld	6	3	3	19
6	Bochum	5	3	2	25
7	Bremen	7	3	4	45
8	Cologne	13	7	6	32
9	Dortmund	7	5	2	42
10	Duisburg	4	3	1	15
11	Frankfurt	9	8	1	30
12	Freiburg	4	1	3	30
13	Hamburg	11	9	2	46
14	Hannover	6	5	1	27
15	Hertha Berlin	8	8	0	30
16	Hoffenheim	5	3	2	13
17	Kaiserslautern	7	5	2	31
18	Leverkusen	12	8	4	47
19	Mainz	2	1	1	16
20	Mönchengladbach	13	9	4	44
21	Nürnberg	7	4	3	25
22	Rostock	7	5	2	26
23	Schalke	9	6	3	44
24	St. Pauli	3	1	2	8
25	Stuttgart	13	9	4	48
26	Uerdingen	1	1	0	4
27	Unterhaching	1	1	0	4
28	Wattenscheid	1	1	0	2
29	Wolfsburg	10	9	1	38
	Total	∅6.41	∅4.38	∅2.03	$\sum$764

Only teams after application of conditions F and MT.
Unit of observation: Half-season.
Time period: The 21 seasons from 1993/94 - 2013/14.

Table 2: The Bundesliga Teams in the Final Data Set

Moreover, Table 2 shows descriptive information for the 29 teams in our final data set, which illustrates again the frequency of managerial changes: For example, almost 60% of these teams have employed at least five (non-interim) managers. And 20% of the teams have even had at least ten managers during the last 21 seasons. Finally, Figure 1 and Table 3 give further descriptive information concerning the dependent variable *Points* and the spells in our final data. Figure 1 shows the distribution of team performance measured by the average number of points per game in the relevant half-season.

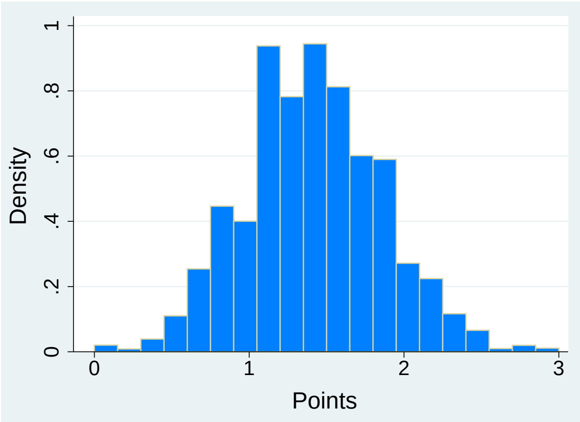


Figure 1: Histogram of dependent variable *Points* (all managers, weighted)

Variable		**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Points	all managers	764	1.410	0.452	0	3
	only movers	533	1.435	0.452	0	3
Matches per spell	all managers	206	58.903	53.483	17	479
	only movers	133	59.872	40.639	17	204
Half-seasons per spell	all managers	206	3.93	3.154	1	29
	only movers	133	4.008	2.404	1	12
Number of spells	all managers	103	1.981	1.350	1	8
	only movers	44	3.159	1.293	2	8

Only teams after application of conditions F and MT.
Points refer to the average number of points per game per half-season, weighted by the number of games of the respective manager-team pair in a half-season.

Table 3: Descriptive Statistics

Note that manager-team pairs win on average 1.41 points per game. On average, a spell lasts for slightly less than 60 matches, and the 103 managers in the final data set are observed with about two spells on average, but this number can be as large as eight.

3 Empirical Analysis

We now investigate whether the identity of the managers indeed has a significant impact on the team's performance. In a first step, we follow Bertrand and Schoar (2003) and start with analyzing the joint effect of managers and teams on the outcome variable and whether and to what extent the explanatory power of the regressions increases once

	Model 1	**Model 2**	**Model 3**
Half-Season FE	Yes	Yes	Yes
Team FE	No	Yes	Yes
Manager FE	No	No	Yes
N	764	764	764
R^2	0.007	0.355	0.469
adj. R^2	-0.049	0.291	0.316
F-test Manager FE			8.633
p-value			0.000

Dependent variable: Average points per game per half-season. Clustered on half-season level, weighted with the number of matches per manager-team pair in half-season

Table 4: The Joint Impact of Managers on Team Performance

manager fixed effects are included (section 3.1). In a next step, we analyze the coefficients of the individual manager fixed effects in more detail (section 3.2).

3.1 The (Joint) Impact of Managers on Team Performance

Table 4 shows the results of three different models which differ with respect to the set of independent variables used. Model 1 contains only half-season fixed effects, Model 2 contains both half-season and team fixed effects, while in Model 3 manager fixed effects are included in addition. As can be seen, the explanatory power sharply increases once team fixed effects are included (Model 2). When comparing Models 2 and 3, the inclusion of manager fixed effects leads to an increase of the R^2 by 11.4 percentage points (or 32.1%), and the adjusted R^2 increases by 2.5 percentage points (or 8.6%). Moreover, the F-Test for the joint significance of the manager fixed effect s is highly significant ($p < 0.01$).

3.2 Estimation of Manager Fixed Effects: Comparing the Performance Contributions of Managers

We now analyze the individual manager fixed effects in more detail. As explained above and analogous to the argument by Abowd et al. (1999), manager fixed effects can be estimated not only for the 44 movers in our sample, but also for the 59 non-movers (such as Pep Guardiola, Luis van Gaal) as long as their only team is also observed with at least one mover, i.e., satisfies condition MT. Note however, that the identification of the fixed effect of non-movers must come from disentangling it from the fixed effect of their (only) team. This might be problematic if this team is only observed with a few other managers. In contrast, for movers we can exploit the larger variation since several teams and their respective team fixed effects are involved. Consequently, we first focus our discussion on the fixed effects for the mover managers.

Table 5 presents the estimated fixed effects for the 44 mover managers in our final sample, ranked by the size of the coefficient which, for each manager, measures his deviation from a reference category. In general, which of the coefficients for the fixed effects are statistically significant depends on the choice of the reference category, and in Table 5 the median manager (Bruno Labbadia) is chosen. In this case, the (statistically significant) coefficient for Jürgen Klopp (rank 1 on left part of Table 5) implies that *ceteris paribus* his teams have won on average 0.46 points per match more than a team coached by a manager of median ability.[12] This performance increase corresponds to 33% of the 1.41 points awarded on average per game during a half-season (see Table 3), and hence would on average lead to an additional $17 \cdot 0.46 = 7.82$ points per half-season for the respective team.[13] For the season 2012/13, for example, this amount of additional points won would have pushed a team from rank 13 to rank 4, which would have allowed the team to participate in the highly prestigious and financially attractive UEFA Champions League.

[12]Of course, each individual fixed effect is estimated with some noise. When comparing the estimates for the individual fixed effects to the median manager only the effect of Jürgen Klopp is statistically different from the median manager. When moving the reference category downwards the number of significant coefficients at the top increases. For example, when compared to a manager at the lower 25% percentile, the coefficients of the top four managers are significant. Furthermore, a large number of pairwise comparisons of managers also exhibit statistically significant differences.

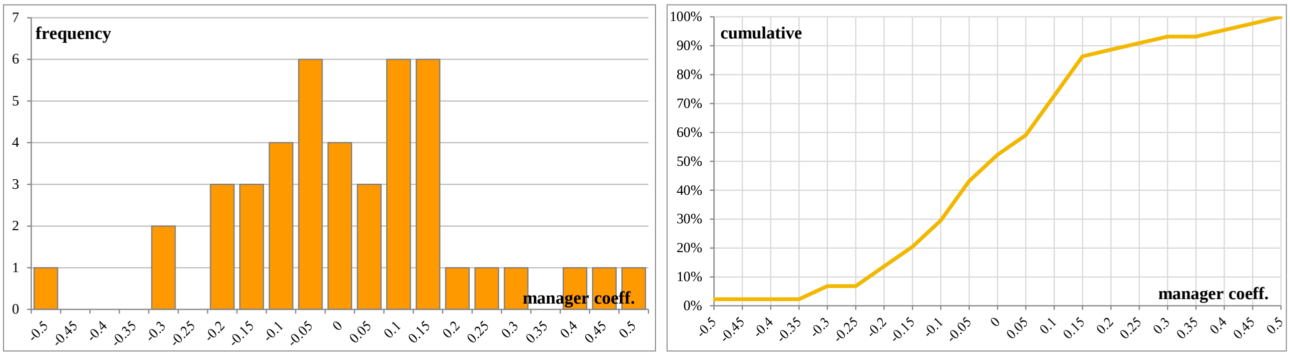
[13]The top rank for Klopp (currently manager of the Premier League team FC Liverpool) seems reasonable, as he was very successful with his first Bundesliga team (the underdog Mainz), and has then led Dortmund to two national championships and to the final of the UEFA Champions League.

	Estimated Fixed Effect			*Average Points Won Per Match°*	
Rank	**Manager**	**Coeff.**	**Rank**	**Manager**	**Avg. Points**
1	Klopp, Jürgen	0.459**	1	Hitzfeld, Ottmar	2.008
2	Favre, Lucien	0.411	2	Trapattoni, Giovanni	1.820
3	Slomka, Mirko	0.378	3	Heynckes, Jupp	1.788
4	Hecking, Dieter	0.264	4	Sammer, Matthias	1.759
5	Rehhagel, Otto	0.202	5	Rehhagel, Otto	1.729
6	Sammer, Matthias	0.164	6	Klopp, Jürgen	1.712
7	Götz, Falko	0.148	7	Daum, Christoph	1.687
8	Heynckes, Jupp	0.146	8	Magath, Felix	1.644
9	Röber, Jürgen	0.127	9	Slomka, Mirko	1.556
10	Magath, Felix	0.121	10	Favre, Lucien	1.545
11	Rangnick, Ralf	0.114	11	Stevens, Huub	1.530
12	Meyer, Hans	0.112	12	Doll, Thomas	1.508
13	Neururer, Peter	0.098	13	Röber, Jürgen	1.496
14	Hitzfeld, Ottmar	0.097	14	Rausch, Friedel	1.481
15	Daum, Christoph	0.078	15	Skibbe, Michael	1.473
16	Veh, Armin	0.073	16	Labbadia, Bruno	1.439
17	Stevens, Huub	0.067	17	Ribbeck, Erich	1.431
18	Lienen, Ewald	0.053	18	Rangnick, Ralf	1.425
19	Köstner, Lorenz-Günther	0.040	19	Jara, Kurt	1.384
20	Babbel, Markus	0.035	20	Veh, Armin	1.367
21	Rausch, Friedel	0.018	21	Hecking, Dieter	1.362
22	Labbadia, Bruno	0 (Ref)	22	Toppmöller, Klaus	1.360
23	Bongartz, Hannes	-0.009	23	Götz, Falko	1.356
24	Doll, Thomas	-0.014	24	Babbel, Markus	1.321
25	Stanislawski, Holger	-0.042	25	Augenthaler, Klaus	1.317
26	Pagelsdorf, Frank	-0.051	26	Pagelsdorf, Frank	1.303
27	Funkel, Friedhelm	-0.058	27	Berger, Jörg	1.299
28	Skibbe, Michael	-0.066	28	Gerets, Eric	1.289
29	Toppmöller, Klaus	-0.073	29	Neururer, Peter	1.287
30	Wolf, Wolfgang	-0.079	30	Wolf, Wolfgang	1.284
31	Jara, Kurt	-0.084	31	Meyer, Hans	1.240
32	Koller, Marcel	-0.119	32	Dutt, Robin	1.215
33	Augenthaler, Klaus	-0.127	33	Lienen, Ewald	1.203
34	Fach, Holger	-0.136	34	Möhlmann, Benno	1.164
35	Gerets, Eric	-0.148	35	Köstner, Lorenz-Günther	1.149
36	Trapattoni, Giovanni	-0.170	36	Fach, Holger	1.127
37	Dutt, Robin	-0.171	37	Bongartz, Hannes	1.113
38	Berger, Jörg	-0.174	38	Funkel, Friedhelm	1.087
39	Rapolder, Uwe	-0.217	39	Koller, Marcel	1.053
40	Frontzeck, Michael	-0.225	40	Rapolder, Uwe	1.041
41	Luhukay, Jos	-0.240	41	Luhukay, Jos	1.022
42	Möhlmann, Benno	-0.333	42	Reimann, Willi	1.017
43	Reimann, Willi	-0.342	43	Stanislawski, Holger	0.981
44	Ribbeck, Erich	-0.514*	44	Frontzeck, Michael	0.942

° *Average Points Won Per Match* refers to the average number of points gained in spells satisfying conditions F and MT.
Significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: Ranking of Mover Managers. Fixed Effects Versus Average Points Won

For the sake of comparison, the right part of Table 5 ranks the managers simply with respect to the average number of points won with their respective teams in the considered spells. As is evident, this procedure favors those managers who have worked for the big teams such as Bayern Munich, Borussia Dortmund or Schalke 04, which have more financial resources to hire the best players. Comparing these two rankings leads to remarkable differences: For example, Giovanni Trapattoni is ranked second using this



(a) Frequency of coefficients (b) Cumulative distribution of the coefficients

Figure 2: Frequency and Distribution of Manager Fixed Effects

simple procedure, while our empirical analysis suggests that his quality is below average (rank 36). On the other hand, we find a strongly positive value for Dieter Hecking (rank 4), who has less experience with top teams, and hence is only listed at position 21 in the ranking purely based on points won. Overall, the correlation between the two measures of ability is not too high ($\rho = 0.5$).

Figure 2 shows the distribution of fixed effects as reported in the left column of Table 5. The histogram depicted in panel a) suggests that Bundesliga managers are quite heterogeneous with respect to their abilities, giving rise to a difference of up to 1 point per match between the managers at the top and the bottom of the ranking. Moreover, as can be seen from the cumulative distribution depicted in panel b), managers around the 80% ability percentile (Jupp Heynckes or Jürgen Röber) gain on average 0.30 points per game more than those at the 20% percentile (Giovanni Trapattoni or Eric Gerets). This corresponds to a difference of 18% of the average number of 1.41 points won per game (see Table 3). In general, many (but not all) of these fixed effects are statistically different from each other in a pairwise comparison.

In summary, our results are in line with previous results from other industries such as Bertrand and Schoar (2003) and Graham et al. (2012) who find that executives are an important factor determining organizational performance. Moreover, the degree of heterogeneity between individuals with respect to this ability seems remarkable, in particular as we take into account only the top segment of the labor market for football managers, i.e. our sample of managers already contains a selected group of the most able ones as each single year, only 24 new managers complete a mandatory training program for head coaches organized by the German Football Association (DFB). All in all, our results do not support the argument that such mandatory training programs would make the population of Bundesliga managers quite homogenous (see e.g., Breuer and Singer, 1996).

Furthermore, our results indicate that the sporting and financial implications of decisions concerning the hiring of managers can be substantial: for example, 33 out of the 63 teams which were either directly relegated to the second division or had to play an additional relegation round to avoid relegation, would have been saved from relegation respectively the relegation round if they had won 5 additional points in the course of the season.[14] According to our analysis, this corresponds to the difference between a manager at the 20%- and 50%-percentile.

Table 13 in Appendix A reports also the fixed effects estimates for non-mover managers (in grey), i.e. those that we observe only with a single team (and where this team satisfies condition MT). As argued by Abowd et al. (1999), these fixed effects are also identified, but the estimates rely on a precise estimation of the respective team fixed effects. This seems a strong requirement for those teams who are observed with only a few other managers (mostly non-movers themselves). Given the few sources of variation and the small number of observations in such cases, the disentangling of the two fixed effects does not always seem convincing and leads to implausible results. Two cases in point here are Thomas Tuchel (Mainz) and Peter Pacult (1860 Munich) whose manager fixed effects seem excessively high (rank 1 and 3, respectively, in Table 13) in the light of their accomplishments.[15] In contrast, as can be seen from Table 14 (also in Appendix A), the estimated team fixed effects for their teams Mainz and 1860 Munich (left column)

[14]From 1993/94 to 2007/08 the last three teams were relegated directly to the second division. As of season 2008/09, the team ranked third to last and the team ranked third in the second division compete in two extra matches for the final Bundesliga slot for the next season.

[15]As of season 2015/16, Thomas Tuchel is the manager of Borussia Dortmund and hence by now a mover, but this season is not contained in our data set.

appear to be excessively low (rank 29 and 26, respectively) compared to the performance of these teams measured in terms of points won (rank 11 and 13, respectively, right column). Hence, the estimates for such non-mover managers that were employed by teams that did not employ many movers have to be interpreted with caution.

4 Robustness

In this section, we check the robustness of our results. First, we cross-validate our estimates of the managers' abilities, by analyzing whether the estimated fixed effects are able to predict future performance (section 4.1). Second, we also consider time-variant proxies for the teams' budgets in the regressions (section 4.2). [16]

4.1 Cross Validation: Predicting Future Performance

As a first robustness check, we check whether our estimates of manager fixed effects are useful in predicting future team performance. In particular, we ask the following question: if we use our approach to obtain estimates of managers' abilities using all the data up to a certain date t which corresponds to the beginning of a season – to what extent do these estimates help to predict performance of the teams employing these managers in the season that follows? In order to do so, we proceed in several steps: First, starting with the beginning of season 2004/05 (which corresponds to half-season 23 in our data set) we estimate manager and team fixed effect s restricting the data set to all outcomes prior to the season we want to predict. Hence, for each manager k and team i and date $t \in \{23, 25, 27, ..41\}$, we obtain a moving time series of fixed effects $\hat{\lambda}_k^{t-1}$ and $\hat{\gamma}_i^{t-1}$ up to date $t-1$. We then run a simple OLS regression with the average number of points obtained by a team in a half-season $t \geq 23$ as the dependent variable and the fixed effects for managers and teams (evaluated at the end of the previous full season) as independent variables.

[16] Instead of half-seasons, we have also used full seasons as the time horizon for which team performance is measured, and the results are almost identical.

	Model P1	Model P2		Model P3	Model P4
Team FE	0.660***	0.782***	*Team Points*	0.962***	0.933***
	(0.0983)	(0.100)		(0.103)	(0.119)
Manager FE		0.354***	*Manager Points*		0.0554
		(0.0891)			(0.114)
Constant	1.354***	1.364***	Constant	0.0861	0.0460
	(0.0301)	(0.0294)		(0.148)	(0.169)
Obs.	262	262	Obs.	262	262
R^2	0.148	0.197	R^2	0.250	0.251
adj. R^2	0.144	0.191	adj. R^2	0.247	0.245

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01. Dependent variable: Average points per game per half-season for the seasons 2004/05 to 2013/14.
In models P1 and P2 the fixed effects for teams and managers are the estimates obtained from season 1993/94 up to the end of the full season preceding the half-season under consideration. Similarly, in model P3 and P4, the average points won by teams and managers are obtained up to the end of the full season preceding the half-season under consideration.

Table 6: Using Fixed Effects to Predict Future Performance

The key question is whether these estimated manager fixed effects have predictive power for the team's performance in the subsequent year. Table 6 shows the regression results, where model P1 includes only our estimates for team strength while in model P2, we add our estimates for managers' abilities. We find indeed that both our measures of team strength and managers' abilities are helpful in predicting subsequent performance. Including our proxies for the managers' abilities raises the adjusted R^2 by 33% from 0.144 to 0.191 and the coefficient of managerial ability is significant at the 1% level. Following Angrist and Pischke (2008) in interpreting regressions as approximations to the conditional expectation function, we thus conclude that our estimates of managerial ability indeed substantially affect conditional expectations and are thus valuable predictors of future performance.

We also compare these predictive regressions to an alternative way of predicting team performance on the basis of the average number of points won by a team (with all its previous managers) and its current manager (with all his previous teams) in the past. While the average number of points won by teams in the past is indeed a valuable predictor for future performance (Model P3), the average number of points won by its manager in the past has no additional explanatory power at all (Model P4). Hence, if we want to disentangle the contribution of a manager from the underlying strength of a team to predict the team's performance, our "purged" measure of ability is more valuable than measures which are simply based on past performance outcomes.[17] Last, but not least, it is interesting to note that the slope of the manager rank (0.354) attains a value of about 45% of the slope of the team strength (0.782). Given that it seems much easier to replace a manager with a better one than to replace a whole team, picking a better manager indeed seems to be a key lever to increase team performance.

4.2 Testing the Impact of Further Time-Variant Variables

The model specification used in section 3 was very parsimonious in the sense that it included only various (time-independent) fixed effects, but not time-variant variables such as a team's wage bill or its (relative) budget, both of which have been shown to also be crucial determinants of team performance (see e.g., Szymanski and Smith, 1997; Hall et al., 2002; Kahane, 2005). As explained above, the main reason for excluding such variables in our basic model was our concern that in the context of determining the value of managers, a team's budget in a given season will also depend on its performance in previous seasons, and hence be influenced by its manager (in case he was already in charge of the team then), so that it is not an independent control variable. For example, a top-5 team in season t is allowed to compete in the UEFA competitions (Champions League and Europa League) in season $t + 1$, which typically comes with a considerable increase in revenues.[18]

But of course the drawback of this parsimonious approach is that idiosyncratic variations in a team's financial strength over the time horizon considered are not accounted for. Hence, managers who are hired in a phase where a team has less financial resources may be disadvantaged and those that are hired in a phase where the team has more resources may benefit as variation in financial strength may be captured by the estimated

[17]The results are robust when replacing the estimated fixed effects of managers and teams as estimated up to date $t - 1$ with their respective percentile scores (i.e. the manager with the highest fixed effect at date $t - 1$ has a percentile score of 1 and the median manager a percentile score of 0.5).

[18]For instance, according to the publicly available Deloitte report "Commercial breaks. Football Money League", Bayern Munich received 44.6 million Euro from the UEFA alone for its Champions League participation in the season 2013/14 (excluding additional gate revenues of approximately 22 million Euro), while the average budget of a Bundesliga team was 41.5 million Euro.

manager fixed effects. To check the robustness of our results, we now also include a proxy for the (relative) budgets of teams in a given season as a time-variant variable.[19] In contrast to the English Premier League where many teams are publicly listed companies, this is not the case for the Bundesliga. Hence, they are not obliged to publish any hard financial information such as budgets or even wage bills. As a consequence, when including (relative) team budgets in the regressions, we must rely on estimates compiled by public sources such as newspapers and specific reports from banks and consulting firms. These are based on core parts of a team's income such as TV revenues, revenues from participation in the UEFA Leagues, ticket sales, and sponsoring which are in large parts publicly available. Hence, while being noisy they do reflect the relative financial strengths of the teams in a given season.[20]

From this information, we have constructed a new variable (*Budget*) which measures a team's relative budget in a given season as the ratio between its absolute budget and the average budget of all teams in that season. Table 7 provides some descriptive statistics on this new variable. As can be seen, Bundesliga teams are quite heterogeneous with respect to their financial possibilities, and some teams such as Bayern Munich (Freiburg) have consistently high (low) budgets and even the minimum (maximum) value is above (below) average. Moreover, the fact that several teams such as Wolfsburg, Leverkusen or Mönchengladbach exhibit minimum values smaller than one and maximum values larger than one suggests that their relative strength also has changed over time.

In Table 8, we report again two model specifications, where a team's relative budget is used in addition to (Model 4) and instead of (Model 5) team fixed effects, respectively. For the sake of comparison, the left column reports again the respective result from

[19] We also investigated the role of further time-variant variables such as a manager's age and tenure but when including them as additional control variables in the regressions, the respective coefficients are virtually zero and statistically insignificant.

[20] In the *Bundesanzeiger*, Germany's official federal gazette regarding all public financial and legal statements made by firms, we found some 25 data points on wage bills (entire staff), and the correlation between these official numbers and our estimates is 0.979. Alternatively, one could use the market value of team rosters based on the estimates on the web page www.transfermarkt.de. While this information is only available for a subset of seasons (from 2005/06 - 2013/14), the correlation with our team budget proxies is 0.87. We are grateful to an anonymous referee for suggesting this alternative measure.

	Team	Relative budget Min.	Max.	Av.		Team	Relative budget Min.	Max.	Av.
1	1860 Munich	0.69	1.08	0.91	16	Hoffenheim	0.72	1.11	0.87
2	Aachen	0.43	0.43	0.43	17	Kaiserlautern	0.39	1.55	0.89
3	Augsburg	0.41	0.46	0.43	18	Leverkusen	0.76	1.38	1.08
4	Bayern Munich	1.24	3.37	2.01	19	Mainz	0.4	0.73	0.57
5	Bielefeld	0.42	0.81	0.63	20	Mönchengladbach	0.69	1.33	0.91
6	Bochum	0.47	0.81	0.64	21	Nürnberg	0.33	1.33	0.66
7	Bremen	0.84	1.44	1.12	22	Rostock	0.53	0.96	0.71
8	Cologne	0.63	1.45	1.05	23	Schalke	1.03	2.21	1.44
9	Dortmund	0.8	1.64	1.23	24	St. Pauli	0.42	0.7	0.58
10	Duisburg	0.55	0.85	0.71	25	Stuttgart	0.92	1.41	1.15
11	Frankfurt	0.64	1.21	0.91	26	Uerdingen	0.41	0.59	0.5
12	Freiburg	0.37	0.75	0.58	27	Unterhaching	0.39	0.48	0.44
13	Hamburg	0.69	1.96	1.14	28	Wattenscheid	0.49	0.49	0.49
14	Hannover	0.62	0.88	0.75	29	Wolfsburg	0.59	1.85	1.22
15	Hertha Berlin	0.55	1.64	1.04					

Only teams after application of conditions F and MT. Sources: Estimates for the 21 seasons from 1993/94 - 2013/14 from the German daily newspapers *Die Welt* (1993/94 to 1998/1999 and 2002/2003 to 2008/2009) and *Rheinische Post* (2007/2008 to 2013/2014) and study "FC Euro AG" (1997/1998 to 2004/2005) published in 2004 by *KPMG* and *WGZ-Bank*.

Table 7: Summary Information for Relative Budgets of Bundesliga Teams

the basic analysis without the relative budget proxies (see right column of Table 4). As can be seen, the manager fixed effects remain also jointly significant at very high significance levels when the budgets are included. Moreover, also the budgets alone have a significant impact, but the adjusted R^2 is higher when team fixed effects are included in addition. Overall, compared to the baseline specification of Model 3, Model 4 leads to a slight increase of the explanatory power, while it decreases under Model 5. This suggests that budget proxies and team fixed effects provide to some extent complementary information. For instance, budgets indeed capture time variation in financial strength, but team fixed effects rather the more stable properties of teams and their management.

We investigate next whether also our estimates for the individual manager fixed effects are robust when we include the budget proxies in addition to team fixed effects (Model 4). The resulting ranking of manager fixed effect s is shown in the right column of Table 9. Again, for the sake of comparison, the left column repeats the ranking from the basic model (see left column of Table 5 above). As can be seen, the ranking of managers is not altered substantially: The ranks of the top managers are virtually unchanged, and

	Model 3	Model 4	Model 5
Half-Season FE	Yes	Yes	Yes
Team FE	Yes	Yes	No
Manager FE	Yes	Yes	Yes
Budget	No	Yes	Yes
N	764	764	764
R^2	0.469	0.474	0.402
adj. R^2	0.316	0.321	0.263
F-test Manager FE	8.633	6.181	11.75
p-value	0.000	0.000	0.000
F-test Team FE	22.86	11.81	
p-value	0.000	0.000	

Dependent variable: Average points per game per half-season. Clustered on half-season level, weighted with the number of matches per manager-team pair in half-season.

Table 8: The Joint Impact of Managers on Team Performance With Team Budgets Included

	Model 3		Model 4			Model 3		Model 4	
Manager	**R.**	**Coeff.**	**R.**	**Coeff.**	**Manager**	**R.**	**Coeff.**	**R.**	**Coeff.**
Klopp, Jürgen	1	0.459	1	0.542	Bongartz, Hannes	23	-0.009	26	-0.049
Favre, Lucien	2	0.411	2	0.442	Doll, Thomas	24	-0.015	14	0.080
Slomka, Mirko	3	0.378	3	0.383	Stanislawski, Holger	25	-0.042	22	0 (Ref)
Hecking, Dieter	4	0.264	4	0.307	Pagelsdorf, Frank	26	-0.051	28	-0.073
Rehhagel, Otto	5	0.202	6	0.146	Funkel, Friedhelm	27	-0.058	25	-0.047
Sammer, Matthias	6	0.164	5	0.188	Skibbe, Michael	28	-0.066	27	-0.051
Götz, Falko	7	0.148	16	0.070	Toppmöller, Klaus	29	-0.073	32	-0.087
Heynckes, Jupp	8	0.146	15	0.073	Wolf, Wolfgang	30	-0.079	24	-0.016
Röber, Jürgen	9	0.127	8	0.115	Jara, Kurt	31	-0.084	33	-0.098
Magath, Felix	10	0.121	10	0.109	Koller, Marcel	32	-0.119	29	-0.08
Rangnick, Ralf	11	0.114	7	0.126	Augenthaler, Klaus	33	-0.127	31	-0.087
Meyer, Hans	12	0.112	8	0.115	Fach, Holger	34	-0.136	36	-0.143
Neururer, Peter	13	0.098	13	0.084	Gerets, Eric	35	-0.148	37	-0.148
Hitzfeld, Ottmar	14	0.097	12	0.099	Trapattoni, Giovanni	36	-0.17	34	-0.1
Daum, Christoph	15	0.078	20	0.025	Dutt, Robin	37	-0.171	35	-0.133
Veh, Armin	16	0.073	11	0.100	Berger, Jörg	38	-0.174	39	-0.189
Stevens, Huub	17	0.067	19	0.033	Rapolder, Uwe	39	-0.217	41	-0.23
Lienen, Ewald	18	0.053	17	0.067	Frontzeck, Michael	40	-0.225	40	-0.204
Köstner, Lorenz-Günther	19	0.040	21	0.023	Luhukay, Jos	41	-0.24	38	-0.16
Babbel, Markus	20	0.035	18	0.061	Möhlmann, Benno	42	-0.333	43	-0.326
Rausch, Friedel	21	0.018	30	-0.081	Reimann, Willi	43	-0.342	42	-0.274
Labbadia, Bruno	22	0 (Ref)	23	-0.005	Ribbeck, Erich	44	-0.514	44	-0.544

In Model 4, the coefficient of the variable *Budget* is 0.167** ($p < 0.058$).

Table 9: Ranking of Fixed Effects of Mover Managers Without and With Team Budgets

also their coefficients are very similar. Overall, Spearman's rank correlation coefficient between the ranking with and without budget proxies is $\rho = 0.97$, suggesting that our results are indeed robust in this respect. In contrast to the above-mentioned scepticism by Kuper and Szymanski (2009) concerning the contribution of managers in determining team performance on top of teams' financial power, our results suggests that there is indeed a role for managers (at least in the Bundesliga), even after controlling for the (time-variant) financial strength of teams.

5 Manager Fixed Effects and Team Style

Apart from team performance, managers might also have an impact on other team variables such as a team's playing style, in particular whether it is playing rather offensively or defensively.[21] Consequently, we can apply the same method as in the above in order to analyze to what extent the identity of the manager in office has predictive power to explain a team's playing style. To this end, we start by defining the following measure of "offensiveness" of team i under manager k in half-season t:

$$\text{Offensive}_{ikt} = \frac{\text{average goals scored per match}}{\text{average points won per match}} \tag{2}$$

Under this measure, a team is considered to play more offensively when it scores more goals for a given average number of points won.[22] Analogously to the analysis of team performance, we first investigate whether the manager fixed effects are jointly significant in determining the playing style of teams, and the results are reported in Table 10.

As before, the goodness of fit increases by a large amount when adding team - and manager fixed effects (comparing Models S1 and S2 versus Model S3), respectively. Moreover, the increase is particularly large when manager fixed effects are added, while the addition of team fixed effects alone has only a small impact. This suggests that

[21]Further dimensions of interest would be how aggressively teams play (as for example measured by the number of yellow and red cards conceded), or their physical activity level in the pitch (as for example measured by the average number of kilometers which players run during a match). Unfortunately, our data set does not contain the respective information.

[22]For example, when a match ends in a 3 : 3 tie, both teams would be considered to play more offensively than under a 0 : 0 tie (both outcomes resulting in one point won for each team). Note that for the league table at the end of the season, the crucial variable is the number of points won, while the difference between the numbers of goals scored and goals conceded is used as a tie-breaking rule. Given the large number of 34 match days, however, ties of this type occur only very rarely.

	Model S1	**Model S2**	**Model S3**
Half-Season FE	Yes	Yes	Yes
Team FE	No	Yes	Yes
Manager FE	No	No	Yes
N	753	753	753
R^2	0.045	0.106	0.302
adj. R^2	-0.010	0.015	0.097
F-test Manager FE			14.53
p-value			0.000

Dependent variable: Offensive rating per game per half-season. Clustered on half-season level, weighted with the number of matches per manager-team pair in half-season.

Table 10: The Joint Impact of Managers on Team Style

the degree to which teams are playing offensively is strongly influenced by their current managers rather than "team DNA".[23]

In a next step, we can compare these manager fixed effects with those based on team performance (see Table 4 above). Interestingly, better managers (i.e. those with larger manager fixed effects in our performance regressions) are those who prefer their team to play defensively. Figure 3 depicts the manager fixed effects along these two dimensions, and it reveals a negative correlation between offensive style and performance ($\rho = -0.375$). At an anecdotal level, this is consistent with the frequently heard claim that a good offense is what pleases the audience, while a good defence is what wins titles. Or, as has been concisely put by American Football coach Bear Bryant: "Offense sells tickets, defense wins championships".

6 The Impact of Managers' Background as Professional Players

While the previous analysis was based on the impact of (unobservable) fixed effect of managers, we follow Bertrand and Schoar (2003) and also analyze the impact of *observ-*

[23] Again, managers can also be ranked with respect to their estimated fixed effects with respect to the offensive style of their teams. This ranking is available from the authors upon request.

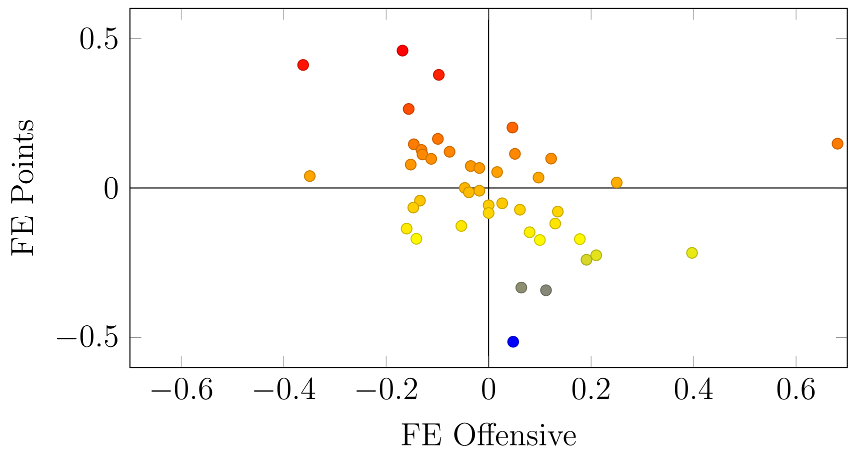


Figure 3: Relation Between Managerial Impact on Performance and Team Style

able characteristics of the managers on team performance. In particular, we focus on characteristics which are related to a manager's previous career as a professional player before becoming a manager. For example, in professional basketball (NBA) Goodall et al. (2011) find evidence that former NBA top players indeed make better coaches. For the case of soccer, to the best of our knowledge this issue has not yet been addressed in previous academic work. But there is a current public debate about whether or not a good manager needs the right "pedigree" (such as being a former star player or even winner of the World Cup) or whether what really counts is a thorough understanding of the game beyond own playing experience (e.g., in terms of tactics, team leadership and motivation, up-to-date expert support staff).[24] Since anecdotal evidence exists on either side, it is interesting to take a more detailed look at this issue.[25] In particular, the following information is available for the managers in our data set (summarized in Table 11: i) whether a manager was a former professional player (*Professional*, ii) whether

[24]For example, Mehmet Scholl, a former star player of Bayern Munich and the German national team, and now an influential TV sports commentator, claims that actual experience as a player matters for being a successful coach. In a recent interview with the leading German weekly magazine *Der Spiegel* he complains about managers who have not been successful players themselves as "... they have never played at the top level, and they have no clue how players at this level operate [...] It is all about tactics, these are mere laptop managers." (see Der Spiegel, Issue 37/2015, pp. 100).

[25]For example, while protagonists such as Franz Beckenbauer, Jupp Heynckes or Matthias Sammer were quite successful as both players and managers, in our ranking reported in Table 4, four out of the five top managers never made it to the Bundesliga or to some other top league.

he was formerly playing in his respective national team (*National*) and iii) a dummy variable whether he played on an offensive position (*Off-position*).[26]

Manager type	**Total**	***Professional***	***National***	***Off-position***
All managers	103	89	41	41
Only movers	44	39	17	22

Table 11: Managers' Background as a Professional Player

The results for the different categories are reported in Table 12 (note that none of the regressions includes manager fixed effects):[27]

As can be seen, the teams of managers who were former professional players do worse than those of managers who were not. This holds irrespective of whether teams are approximated by team fixed effects only (Model O1) or when budget are included in addition (Model O2). Overall, the results provide evidence for a potential overrating of prominent names in the hiring process of managers. Another interpretation is that managers who have not been former star players themselves need to be substantially better coaches in order to secure a job as a head coach in the top leagues. The latter must start their manager career in low divisions and hence, when such managers are promoted to top-tier teams, they have already proven to possess some manager quality beforehand; otherwise they would not have made to a top division team. In contrast, former professionals often start their manager careers directly in the Bundesliga or second division without any significant prior manager experience, where prominent example include Franz Beckenbauer, Jürgen Klinsmann (both Bayern Munich) and Matthias Sammer (Dortmund). In these cases, inferior manager quality only shows up *after* they have taken over a top division team (thereby entering our data set).[28] Such a mechanism

[26]As in the regressions of section 4.2, there is no significant effect of manager tenure and/or age on the results when including them as additional control variables.

[27]We have also investigated the impact of these manager characteristics on the offensive style of their teams, and there is no effect. The results are available from the authors on request.

[28]Of course, teams may nevertheless have an incentive to hire big names, because there might be other benefits (e.g., increased media attention or higher match attendance) associated with it.

	Model O1	Model O2	Model O3	Model O4
Professional	-0.107**	-0.100**		
	(0.047)	(0.048)		
National			-0.010	
			(0.038)	
Off-position				-0.015
				(0.030)
Budget	-	0.180***	-	-
		(0.059)		
Constant	1.395***	1.224***	1.294***	1.303***
	(0.075)	(0.102)	(0.066)	(0.066)
N	764	764	764	764
R^2	0.359	0.371	0.355	0.355
adj. R^2	0.294	0.306	0.290	0.290
F-test Team FE	37.46	17.11	30.18	33.55
p-value	0.000	0.000	0.000	0.000

Dependent variable: Average points per game per half-season. Fixed effects for half-seasons and teams included in all regressions. Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01. Clustered on half-season level, weighted with the number of matches per manager-team pair in half-season.

Table 12: Impact of Managers' Background as Professional Players on Team Performance

might also explain why our findings are qualitatively different than those of Goodall et al. (2011). In the NBA, it seems that the typical career path of former star players involves first a lower-level position such as assistant coach, and only the successful ones become eventually promoted to head coach.[29] Finally, we find no effect on performance for managers being a former member of a national team, or the position in which they used to play (see Models O3 and O4).

7 Conclusion

We have analyzed the impact of managers on the performance of their teams in the context of professional sports. In particular, we have estimated average additional performance contributions for individual managers by making use of the high turnover rates in the Bundesliga which allows to disentangle manager effects from the strength of their

[29] For example, for the upcoming NBA season 2016/17, 13 out of 30 head coaches have been former NBA players, and 11 out of these held other coaching positions in basketball before taking over their first position as a NBA head coach.

respective teams. We found a considerable variation in these performance contributions. Moreover, we have also documented an impact of managers on teams' style of playing, and we show that once famous and successful players do not necessarily make good managers later on in their careers.

Of course the approach also has potential limitations. For example, one could argue that the estimate for managers in top teams like Bayern Munich are computed comparing them only with other top managers while managers in bad teams are compared only with lower qualified managers. However, we observe a substantial number (26) of managers who have worked in teams of very different strengths. For instance, one manager (Felix Magath) has worked in 7 different teams (including Bayern Munich, but also substantially weaker ones such as Nürnberg or Frankfurt). These high frequency movers connect managers across different skill levels and facilitates the identification of their individual effects (see also the argument in Graham et al., 2012). But of course, the individual ability estimates have to be treated with caution for those managers who have worked only in teams which have employed only a few other managers.

A potentially more problematic assumption is the stability of the (relative) strengths of teams across the considered time period which may vary over time due to changes in the financial strength of teams. But as we have shown, the estimated manager fixed effects remain rather stable when we include time-varying information such as the relative budgets of the teams in a given season. A further possibility to address the issue of time-invariance would be to divide the 21 seasons of our data set into shorter time intervals (for example, by including team/season fixed effect vs covering, say, five seasons). However, apart from the fact that any such division of our data set into 5-year periods would appear arbitrary to some degree, this also raises collinearity issues due to a larger congruence of the time periods in which manager-team pairs are observed. For example, when a manager is observed with a team for a whole five-year period, then part of his impact will be picked up by the respective team/season fixed effect and vice versa.

Moreover, we have shown that our ability estimates have predictive power. Using past data to estimate abilities disentangling manager's contributions helps to form better expectations about future performance. In turn, it can help teams to spot talent and to detect undervalued managers on the market.

Appendix

A Estimated Fixed Effect for All Managers (Movers and Non-movers)

The subsequent table provides a ranking of all (mover and non-mover) managers in the final data set.

Estimated Fixed Effects						Avg. Points per Game					
Rank	**Manager**	**Coeff.**	**Rank**	**Manager**	**Coeff.**	**Rank**	**Manager**	**∅Points**	**Rank**	**Manager**	**∅Points**
1	Tuchel, Thomas	0.829	53	Sidka, Wolfgang	-0.019	1	Guardiola, Pep	2.647	53	Berger, Jörg	1.299
2	Guardiola, Pep	0.694	54	Solbakken, Stale	-0.028	2	Hitzfeld, Ottmar	2.008	54	Lorant, Werner	1.291
3	Pacult, Peter	0.552	55	Gaal, Louis van	-0.028	3	Lewandowski, Sascha	1.975	55	Gerets, Eric	1.289
4	**Klopp, Jürgen**	0.459	56	**Stanislawski, Holger**	-0.042	4	Gaal, Louis van	1.937	56	Neururer, Peter	1.287
5	Keller, Jens	0.428	57	**Pagelsdorf, Frank**	-0.051	5	Klinsmann, Jürgen	1.862	57	Wolf, Wolfgang	1.284
6	**Favre, Lucien**	0.411	58	**Funkel, Friedhelm**	-0.058	6	Keller, Jens	1.843	58	Fink, Thorsten	1.266
7	Gross, Christian	0.401	59	**Skibbe, Michael**	-0.066	7	Trapattoni, Giovanni	1.820	59	Fringer, Rolf	1.265
8	Jol, Martin	0.379	60	Weinzierl, Markus	-0.070	8	Jol, Martin	1.794	60	Scala, Nevio	1.265
9	Korkut, Tayfun	0.378	61	**Toppmöller, Klaus**	-0.073	9	Heynckes,Jupp	1.788	61	Weinzierl, Markus	1.250
10	**Slomka, Mirko**	0.378	62	**Wolf, Wolfgang**	-0.079	10	Gross, Christian	1.769	62	Meyer, Hans	1.240
11	Lewandowski, Sascha	0.361	63	**Jara, Kurt**	-0.084	11	Sammer, Matthias	1.759	63	Köppel, Horst	1.231
12	Lorant, Werner	0.338	64	Klinsmann, Jürgen	-0.100	12	Rehhagel, Otto	1.729	64	Körbel,Karl-Heinz	1.229
13	Schaefer, Frank	0.333	65	Fink, Thorsten	-0.114	13	Klopp, Jürgen	1.712	65	Dutt, Robin	1.215
14	Schaaf, Thomas	0.314	66	**Koller, Marcel**	-0.119	14	Daum, Christoph	1.687	66	Schlünz, Juri	1.205
15	**Hecking, Dieter**	0.264	67	**Augenthaler, Klaus**	-0.127	15	Löw, Joachim	1.662	67	Lienen, Ewald	1.203
16	Krauss, Bernd	0.257	68	Verbeek, Gertjan	-0.133	16	Hyypiä, Sami	1.655	68	Zachhuber, Andreas	1.180
17	**Rehhagel, Otto**	0.202	69	**Fach, Holger**	-0.136	17	Magath, Felix	1.644	69	Möhlmann, Benno	1.164
18	Löw, Joachim	0.168	70	Vogts, Berti	-0.139	18	Schaaf, Thomas	1.618	70	Finke, Volker	1.162
19	Wiesinger, Michael	0.164	71	Engels, Stephan	-0.140	19	Vogts, Berti	1.591	71	Wiesinger, Michael	1.160
20	**Sammer, Matthias**	0.164	72	Körbel, Karl-Heinz	-0.143	20	Slomka, Mirko	1.556	72	Köstner, Lorenz-Gün..	1.149
21	Olsen, Morten	0.148	73	**Gerets, Eric**	-0.148	21	Brehme, Andreas	1.547	73	Fach, Holger	1.127
22	**Götz, Falko**	0.148	74	**Trapattoni, Giovanni**	-0.170	22	Favre, Lucien	1.545	74	Bongartz, Hannes	1.113
23	**Heynckes, Jupp**	0.146	75	**Dutt, Robin**	-0.171	23	Stevens, Huub	1.530	75	Middendorp, Ernst	1.108
24	Brehme, Andreas	0.133	76	**Berger, Jörg**	-0.174	24	Doll, Thomas	1.508	76	Kurz, Marco	1.100
25	**Röber, Jürgen**	0.127	77	Marwijk, Bert van	-0.185	25	Neubarth, Frank	1.500	77	McClaren, Steve	1.095
26	**Magath, Felix**	0.121	78	Heesen, Thomas von	-0.193	26	Röber, Jürgen	1.496	78	Heesen,Thomas von	1.091
27	Gisdol, Markus	0.116	79	Advocaat, Dick	-0.195	27	Krauss, Bernd	1.487	79	Funkel, Friedhelm	1.087
28	**Rangnick, Ralf**	0.114	80	Middendorp, Ernst	-0.206	28	Rausch, Friedel	1.481	80	Latour, Hanspeter	1.059
29	**Meyer, Hans**	0.112	81	**Rapolder, Uwe**	-0.217	29	Rutten, Fred	1.480	81	Pezzaiuoli, Marco	1.059
30	**Neururer, Peter**	0.098	82	Pezzaiuoli, Marco	-0.217	30	Skibbe, Michael	1.473	82	Koller, Marcel	1.053
31	**Hitzfeld,Ottmar**	0.097	83	**Frontzeck, Michael**	-0.225	31	Pacult, Peter	1.469	83	Maslo, Uli	1.048
32	**Daum, Christoph**	0.078	84	Herrlich, Heiko	-0.234	32	Marwijk, Bert van	1.447	84	Rapolder, Uwe	1.041
33	**Veh, Armin**	0.073	85	**Luhukay, Jos**	-0.240	33	Labbadia, Bruno	1.439	85	Luhukay, Jos	1.022
34	**Stevens, Huub**	0.067	86	Bommer, Rudi	-0.242	34	Ribbeck, Erich	1.431	86	Reimann, Willi	1.017
35	Maslo, Uli	0.066	87	Fringer, Rolf	-0.251	35	Dörner, Hans-Jürgen	1.426	87	Advocaat, Dick	1.000
36	Köppel, Horst	0.064	88	Finke, Volker	-0.268	36	Rangnick, Ralf	1.425	88	Engels, Stephan	1.000
37	**Lienen, Ewald**	0.053	89	Kurz, Marco	-0.275	37	Stepanovic, Dragoslav	1.414	89	Mos, Aad de	1.000
38	Dörner, Hans-Jürgen	0.049	90	Demuth, Dietmar	-0.276	38	Korkut, Tayfun	1.412	90	Soldo, Zvonimir	1.000
39	Streich, Christian	0.044	91	McClaren, Steve	-0.303	39	Tuchel, Thomas	1.406	91	Stanislawski, Holger	0.981
40	**Köstner, Lorenz-Günther**	0.040	92	Oenning, Michael	-0.332	40	Jara, Kurt	1.384	92	Solbakken, Stale	0.967
41	Latour, Hanspeter	0.039	93	**Möhlmann, Benno**	-0.333	41	Veh, Armin	1.367	93	Schneider, Thomas	0.952
42	Schlünz, Juri	0.038	94	**Reimann, Willi**	-0.342	42	Schaefer, Frank	1.364	94	Frontzeck, Michael	0.942
43	Rutten, Fred	0.035	95	Zumdick, Ralf	-0.358	43	Hecking, Dieter	1.362	95	Herrlich, Heiko	0.909
44	**Babbel, Markus**	0.035	96	Scala, Nevio	-0.379	44	Toppmöller, Klaus	1.360	96	Verbeek, Gertjan	0.909
45	Zachhuber, Andreas	0.032	97	Gerland, Hermann	-0.401	45	Götz, Falko	1.356	97	Gerland, Hermann	0.882
46	**Rausch, Friedel**	0.018	98	Schneider, Thomas	-0.421	46	Gisdol, Markus	1.341	98	Zumdick, Ralf	0.857
47	Soldo, Zvonimir	0.017	99	Stepanovic, Dragoslav	-0.424	47	Streich, Christian	1.341	99	Bommer, Rudi	0.853
48	**Labbadia, Bruno**	0 (Ref)	100	Mos, Aad de	-0.452	48	Sidka, Wolfgang	1.333	100	Sorg, Marcus	0.765
49	Neubarth, Frank	-0.003	101	Bonhof, Rainer	-0.466	49	Babbel, Markus	1.321	101	Oenning, Michael	0.706
50	Hyypiä, Sami	-0.003	102	**Ribbeck, Erich**	-0.514	50	Augenthaler, Klaus	1.317	102	Bonhof, Rainer	0.696
51	**Bongartz, Hannes**	-0.009	103	Sorg, Marcus	-0.562	51	Olsen, Morten	1.314	103	Demuth, Dietmar	0.647
52	**Doll, Thomas**	-0.014				52	Pagelsdorf, Frank	1.303			

All managers not eliminated by conditions F and MT.
Non-mover managers are highlighted in gray.

Table 13: Ranking of Mover and Non-Mover Managers by Size of Fixed Effect

Estimated Fixed Effects			*Average Points per Game*		
Rank	**Team**	**Coeff**	**Rank**	**Team**	**Points**
1	Bayern Munich	0.751	1	Bayern Munich	2.082
2	Leverkusen	0.460	2	Dortmund	1.755
3	Dortmund	0.347	3	Leverkusen	1.677
4	Schalke	0.230	4	Schalke	1.604
5	Hamburg	0.207	5	Bremen	1.546
6	Stuttgart	0.177	6	Stuttgart	1.510
7	Augsburg	0.147	7	Hamburg	1.444
8	Wolfsburg	0.147	8	Kaiserslautern	1.444
9	Kaiserslautern	0.143	9	Hertha Berlin	1.418
10	Freiburg	0.117	10	Wolfsburg	1.383
11	Bremen	0.058	11	Mainz	1.301
12	Hertha Berlin	0.033	12	Hannover	1.296
13	Hoffenheim	0.032	13	1860 Munich	1.293
14	Bielefeld	0.015	14	Hoffenheim	1.292
15	Frankfurt	0 (Ref)	15	Mönchengladbach	1.239
16	Bochum	-0.034	16	Frankfurt	1.212
17	Aachen	-0.046	17	Augsburg	1.206
18	Duisburg	-0.116	18	Freiburg	1.178
19	Rostock	-0.124	19	Bochum	1.175
20	Mönchengladbach	-0.128	20	Unterhaching	1.162
21	Unterhaching	-0.142	21	Rostock	1.160
22	Nürnberg	-0.165	22	Duisburg	1.135
23	Hannover	-0.187	23	Nürnberg	1.127
24	Cologne	-0.216	24	Cologne	1.114
25	St. Pauli	-0.353	25	Bielefeld	1.044
26	1860 Munich	-0.354	26	Aachen	1.000
27	Uerdingen	-0.477	27	St. Pauli	0.892
28	Wattenscheid	-0.583	28	Wattenscheid	0.826
29	Mainz	-0.621	29	Uerdingen	0.821

Table 14: Ranking of Teams. Fixed Effects (left) and Average Points per Game (right)

B Managers and Spells Eliminated by Condition F

	Manager		Manager
1	Achterberg, Eddy	31	Krautzun, Eckhard
2	Adrion, Rainer	32	Lattek, Udo
3	Arnesen, Frank	33	Lieberwirth, Dieter
4	Balakov, Krassimir	34	Lippert, Bernhard
5	Beckenbauer, Franz	35	Littbarski, Pierre
6	Bergmann, Andreas	36	Minge, Ralf
7	Brunner, Thomas	37	Moniz, Ricardo
8	Cardoso, Rudolfo	38	Moser, Hans-Werner
9	Dammeier, Detlev	39	Nemet, Klaus-Peter
10	Dohmen, Rolf	40	Neu, Hubert
11	Ehrmantraut, Horst	41	Preis, Ludwig
12	Eichkorn, Josef	42	Prinzen, Roger
13	Entenmann, Willi	43	Reck, Oliver
14	Erkenbrecher, Uwe	44	Renner, Dieter
15	Fanz, Reinhold	45	Reutershahn, Armin
16	Geideck, Frank	46	Rolff, Wolfgang
17	Gelsdorf, Jürgen	47	Schafstall, Rolf
18	Halata, Damian	48	Schehr, Ralf
19	Hartmann, Frank	49	Scholz, Heiko
20	Heine, Karsten	50	Schulte, Helmut
21	Heinemann, Frank	51	Sundermann, Jürgen
22	Henke, Michael	52	Thom, Andreas
23	Hermann, Peter	53	Tretschok, Rene
24	Hieronymus, Holger	54	Vanenburg, Gerald
25	Hrubesch, Horst	55	Völler, Rudi
26	Hörster, Thomas	56	Weber, Heiko
27	John, Christoph	57	Wilmots, Marc
28	Jonker, Andries	58	Wosz, Dariusz
29	Kohler, Jürgen	59	Ziege, Christian
30	Kramer, Frank	60	Zobel, Rainer

Table 15: Managers without a spell satisfying condition F

	Manager	**Team**	**Matches** (in Spell)	**Year**
1	Adrion, Rainer	Stuttgart	11	1998
2	Beckenbauer, Franz	Bayern Munich	14	1993
3	Bergmann, Andreas	Hannover	16	2009
4	Ehrmantraut, Horst	Frankfurt	16	1998
5	Entenmann, Willi	Nürnberg	15	1993
6	Gelsdorf, Jürgen	Bochum	12	1994
7	Götz, Falko	Hertha Berlin	13	2001
8	Hartmann, Frank	Wattenscheid 09	11	1993
9	Heesen, Thomas von	Nürnberg	15	2007
10	Henke, Michael	Kaiserslautern	13	2005
11	Hörster, Thomas	Leverkusen	11	2002
12	Kohler, Jürgen	Duisburg	11	2005
13	Köstner, Lorenz-Günther	Wolfsburg	15	2009
14	Krauss, Bernd	Dortmund	11	1999
15	Krautzun, Eckhard	Kaiserslautern	11	1995
16	Kurz, Marco	Hoffenheim	10	2012
17	Marwijk, Bert van	Hamburg	15	2013
18	Meier, Norbert	Mönchengladbach	11	1997
19	Meier, Norbert	Duisburg	15	2005
20	Minge, Ralf	Dresden	15	1994
21	Oenning, Michael	Hamburg	14	2010
22	Rangnick, Ralf	Schalke	13	2011
23	Rausch, Friedel	Nürnberg	16	1998
24	Rehhagel, Otto	Hertha Berlin	12	2011
25	Reimann, Willi	Nürnberg	15	1998
26	Schäfer, Winfried	Stuttgart	15	1998
27	Schafstall, Rolf	Bochum	13	2000
28	Schulte, Helmut	Schalke	11	1993
29	Slomka, Mirko	Hamburg	13	2013
30	Stevens, Huub	Stuttgart	10	2013
31	Zobel, Rainer	Nürnberg	14	1993

Table 16: Eliminated Spells with at least 10, but less then 17 matches

C Teams Eliminated by Condition MT

	Team	No. of managers	No. of obs	Managers	No. of obs
1	Braunschweig*	1	2	Lieberknecht, Torsten	2
2	Cottbus	3	13	Geyer, Eduard	6
				Prasnikar, Bojan	4
				Sander, Petrik	3
3	Dresden	1	3	Held, Siegfried	3
4	Düsseldorf*	3	7	Meier, Norbert**	2
				Ristic, Aleksandar	3
				Wojtowicz, Rudolf	2
5	Fürth*	1	2	Büskens, Michael**	2
6	Karlsruhe	2	14	Becker, Edmund	4
				Schäfer, Winfried**	10
7	Leipzig	1	2	Stange, Bernd	2
8	Ulm	1	2	Andermatt, Martin	2
		$\sum 13$	$\sum 45$		$\sum 45$

Unit of observation: Half-season
* Some of team's managers are observed with other teams, but these spells do not satisfy condition F.
** Manager observed with several teams, but only one spell satisfies condition F so that manager is not a mover.

Table 17: Teams eliminated by condition MT and their managers

D Ranking of Manager-Fixed Effects With Respect to Team Style

	Model 3					*Model 3*			
	Performance		*Team Style*			*Performance*		*Team Style*	
Manager	**R.**	**Coeff.**	**R.**	**Coeff.**	**Manager**	**R.**	**Coeff.**	**R.**	**Coeff.**
Klopp, Jürgen	1	0.459	42	-0.168	Bongartz, Hannes	23	-0.009	23	-0.018
Favre, Lucien	2	0.411	44	-0.362	Doll, Thomas	24	-0.015	26	-0.039
Slomka, Mirko	3	0.378	30	-0.097	Stanislawski, Holger	25	-0.042	35	-0.134
Hecking, Dieter	4	0.264	40	-0.156	Pagelsdorf, Frank	26	-0.051	19	0.027
Rehhagel, Otto	5	0.202	18	0.047	Funkel, Friedhelm	27	-0.058	21	0.000
Sammer, Matthias	6	0.164	31	-0.099	Skibbe, Michael	28	-0.066	38	-0.147
Götz, Falko	7	0.148	1	0.681	Toppmöller, Klaus	29	-0.073	15	0.061
Heynckes, Jupp	8	0.146	37	-0.146	Wolf, Wolfgang	30	-0.079	7	0.135
Röber, Jürgen	9	0.127	34	-0.131	Jara, Kurt	31	-0.084	22	0 (Ref)
Magath, Felix	10	0.121	29	-0.076	Koller, Marcel	32	-0.119	8	0.13
Rangnick, Ralf	11	0.114	16	0.051	Augenthaler, Klaus	33	-0.127	28	-0.053
Meyer, Hans	12	0.112	33	-0.129	Fach, Holger	34	-0.136	41	-0.16
Neururer, Peter	13	0.098	9	0.122	Gerets, Eric	35	-0.148	13	0.08
Hitzfeld, Ottmar	14	0.097	32	-0.112	Trapattoni, Giovanni	36	-0.17	36	-0.141
Daum, Christoph	15	0.078	39	-0.152	Dutt, Robin	37	-0.171	6	0.178
Veh, Armin	16	0.0732	25	-0.035	Berger, Jörg	38	-0.174	11	0.1
Stevens, Huub	17	0.067	23	-0.018	Rapolder, Uwe	39	-0.217	2	0.397
Lienen, Ewald	18	0.053	20	0.017	Frontzeck, Michael	40	-0.225	4	0.21
Köstner, Lorenz-Günther	19	0.040	43	-0.349	Luhukay, Jos	41	-0.24	5	0.191
Babbel, Markus	20	0.035	12	0.097	Möhlmann, Benno	42	-0.333	14	0.064
Rausch, Friedel	21	0.018	3	0.25	Reimann, Willi	43	-0.342	10	0.112
Labbadia, Bruno	22	0 (Ref)	27	-0.047	Ribbeck, Erich	44	-0.514	17	0.048

Table 18: Ranking of Mover Managers. Performance Versus Team Style

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999): "High wage workers and high wage firms," *Econometrica*, 67, 251–333.

Angrist, J. D. and J.-S. Pischke (2008): *Mostly harmless econometrics: An empiricist's companion*, Princeton University Press, Princeton, NJ.

Audas, R., S. Dobson, and J. Goddard (2002): "The impact of managerial change on team performance in professional sports," *Journal of Economics and Business*, 54, 633–650.

BAMBER, L. S., J. JIANG, AND I. Y. WANG (2010): "What's my style? The influence of top managers on voluntary corporate financial disclosure," *The Accounting Review*, 85, 1131–1162.

BERTRAND, M. AND A. SCHOAR (2003): "Managing with style: The effect of managers on firm policies," *Quarterly Journal of Economics*, 118, 1169–1208.

BREUER, C. AND R. SINGER (1996): "Trainerwechsel im Laufe der Spielsaison und ihr Einfluss auf den Mannschaftserfolg," *Leistungssport*, 26, 41–46.

CARMICHAEL, F. AND D. THOMAS (1995): "Production and efficiency in team sports: An investigation of rugby league football," *Applied Economics*, 27, 859–869.

DAWSON, P. AND S. DOBSON (2002): "Managerial efficiency and human capital: An application to English association football," *Managerial and Decision Economics*, 23, 471–486.

DAWSON, P., S. DOBSON, AND B. GERRARD (2000a): "Estimating coaching efficiency in professional team sports: Evidence from English association football," *Scottish Journal of Political Economy*, 47, 399–421.

——— (2000b): "Stochastic frontiers and the temporal structure of managerial efficiency in English soccer," *Journal of Sports Economics*, 1, 341–362.

DE PAOLA, M. AND V. SCOPPA (2012): "The effects of managerial turnover: Evidence from coach dismissals in Italian soccer teams," *Journal of Sports Economics*, 13, 152–168.

DYRENG, S. D., M. HANLON, AND E. L. MAYDEW (2010): "The effects of executives on corporate tax avoidance," *The Accounting Review*, 85, 1163–1189.

FIZEL, J. L. AND M. P. D'ITRY (1997): "Managerial efficiency, managerial succession and organizational performance," *Managerial and Decision Economics*, 18, 295–308.

FRICK, B. AND R. SIMMONS (2008): "The impact of managerial quality on organizational performance: Evidence from German soccer," *Managerial and Decision Economics*, 29, 593–600.

GOODALL, A. H., L. M. KAHN, AND A. J. OSWALD (2011): "Why do leaders matter? A study of expert knowledge in a superstar setting," *Journal of Economic Behavior & Organization*, 77, 265–284.

GRAHAM, J. R., S. LI, AND J. QIU (2012): "Managerial attributes and executive compensation," *Review of Financial Studies*, 25, 144–186.

HALL, S., S. SZYMANSKI, AND A. ZIMBALIST (2002): "Testing causality between team performance and payroll: the cases of Major League Baseball and English soccer," *Journal of Sports Economics*, 3, 149–168.

HOFLER, R. A. AND J. E. PAYNE (2006): "Efficiency in the National Basketball Association: A stochastic frontier approach with panel data," *Managerial and Decision Economics*, 27, 279–285.

KAHANE, L. H. (2005): "Production efficiency and discriminatory hiring practices in the National Hockey League: A stochastic frontier approach," *Review of Industrial Organization*, 27, 47–71.

KUPER, S. AND S. SZYMANSKI (2009): *Soccernomics*, Nation Books, New York, NY.

LAZEAR, E. P., K. L. SHAW, AND C. T. STANTON (2015): "The value of bosses," *Journal of Labor Economics*, 33, 823–861.

MUEHLHEUSSER, G., S. SCHNEEMANN, AND D. SLIWKA (2016): "The impact of managerial change on performance: The role of team heterogeneity," *Economic Inquiry*, 54, 1128–1149.

ROSEN, S. (1982): "Authority, control, and the distribution of earnings," *The Bell Journal of Economics*, 13, 311–323.

Szymanski, S. and R. Smith (1997): "The English football industry: profits, performance and industry structure," *International Review of Applied Economics*, 11, 135–153.

Tena, J. d. D. and D. Forrest (2007): "Within-season dismissal of football coaches: Statistical analysis of causes and consequences," *European Journal of Operational Research*, 181, 362–373.