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Learning from the Field: Does Sport-Tested Theory Transfer to Business?

Bart Schrama (532580BS)

Supervisor:	Ours, JC van
Second assessor:	Fok, D
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Abstract

This study aims to extend the current academic literature on coach and CEO dismissals by leveraging methods and insights derived from sports-based research. Ultimately, assessing whether sports are a viable proxy to test labour economic theories. This paper uses research based on in-season head-coach dismissals in professional football and compares this against CEO dismissals in S&P1500 firms. Logit regressions are estimated to determine dismissal and change causes for top leadership, followed by regression analysis for various performance metrics, finding significant performance increases after dismissal of both the CEO and Coach. However, since these increases are also found in the control group it is not possible to attribute these increases to the change in leadership. Ultimately, concluding that dismissal of the top executive increases neither team nor firm performance.

1 Introduction

Sports are an integral part of human endeavour, and they also serve as a powerful tool in unlikely places, such as academia, to better understand and analyse real-life situations. By drawing links between sports and business examples, we can find new insights into various previously stated labour theories. This relationship has been explored by academics such as Kahn (2000), who states that sports offer an "unique opportunity for labour market research." In their paper, the author claims that the wider availability of data and clearer datasets of results help bridge the gap between labour theory and real-world tests. Labour theories on CEO dismissals also suffer from this data problem and thus can be tested using sports proxies in the form of head coaches. One argument for this claim is the "Great Person Theory" discussed in Anderson (2013), which argues that the influence of football managers on the team is non-negligible. Based on this, a poorly performing firm or club could be turned around by hiring better management.

This research is important because it acts as a check for the prior statements. Evidently, it checks whether one can really apply the results that were found in the coach-based literature on real-world scenarios in managerial dismissals. To do so, this paper will aim to recreate football-based research and apply the exact same methods to data on CEO dismissals, using similar type variables. This way, achieving the same result in both the managerial field and the sports economic field. The significance of this research thus builds on the significance of papers such as Tena and Forrest (2007) and Dobson and Goddard (2001), who based their findings on football data, ultimately verifying that their introductory assumptions on similarities between CEOs and head coaches were justified. Besides building on these papers, it also reaffirms the methods employed by Van Ours and Van Tuijl (2016) to create better control groups and more accurately test the effects. Furthermore, there is also significant social importance, besides checking the relation between sports and labour economics, sports clubs gain more information on when to fire their manager and what the effects are. Similarly, companies gain information on the effects of firing and can make better decisions on when and if to cut their CEO. For example, bad share price performance was found not to be a good reason to change CEO.

The overarching question that the paper poses and answers is thus: Are the results based on football data comparable to the results based on corporate data? In this paper, this question is answered regarding both the reasons for dismissal as well as the effects of dismissal.

This paper will do this based on a CEO-dismissal dataset with a selected 3,898 changes (772 dismissals) based on the S&P1500 and a coach dismissal dataset with 59 total changes based on the Dutch Eredivisie.

First, logit models are estimated to test what influences the likelihood of dismissal or a quit for both CEOs and coaches. The logit model draws parameters from the literature against the available data and ultimately finds significant similarities in the causes as both models find performance proxies and third-party estimates to be significant. Secondly, matched treatment-control regressions are estimated to identify the effects of a change or dismissal in top management (CEO or coach). This regression matches based on a performance indicator in the match (or month) prior to the recorded change. For the football data, it matches based on the surprise of bookmakers, and for CEO data, it matches based on analyst surprise as well as a combination of analyst surprise and market performance. Again, similar results are found using both methods. Namely, neither has found consequential evidence that there is a performance increase that can be attributed to the dismissal. Moreover, the CEO data even shows that the counterfactual observations have a larger performance increase than the actual changes in management suggesting a negative result.

This research is different from prior research as it is one of the first papers that compares the football-based results against firm-based results. This was only done prior by Ter Weel (2011), which suggests that there is explanatory power in the methodology of the sports-based papers. The aim of this study is to reinforce these findings by providing additional support through a comparison of the results obtained by Van Ours and Van Tuijl (2016) with the American S&P1500 dismissals. The main difference to Ter Weel is that I use much newer data and better control groups based on individual matching.

Ultimately, the conclusions drawn from this research align with the existing literature. Specifically, the study finds that the dismissal of football coaches does not exert a significant impact on team performance, which underlines the findings of prior studies. Similarly, with regard to CEO dismissals, the analysis reveals that they do not lead to a substantial performance improvement compared to the control group. However, I do observe a slight decline in performance relative to the control group, suggesting that CEO dismissals indeed do harm the company and imply structural problems, again in accordance with the prior literature.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive overview of the existing literature concerning coach and CEO changes. Section 3 describes the data and outlines the cleaning and selection procedures. In Section 4, I will discuss the methodologies applied to construct the complete dataset and test the hypothesis. Section 5 presents the research findings, focusing on the causes for dismissal and the effects of dismissal. Finally, Section 6 contains the conclusions drawn from the findings and discusses the study's limitations and potential avenues for future research.

2 Theoretical Framework

Maximizing managerial efficiency is crucial for achieving optimal outcomes and driving performance in organizational contexts. In the case of CEO and coach succession, replacing an inefficient incumbent with a more qualified leader might be necessary. Sometimes, the current manager may be suboptimal due to inadequate skills, lack of strategic vision, or poor decision-making. In such instances, a managerial change is essential to improve performance. Based on this, one can argue the importance of managerial changes in influencing organizational outcomes. The paper by Hambrick (1991) on the seasons of a CEO's tenure provides valuable insights into the impact of managerial leadership on firm performance. By examining different stages of a CEO's tenure, Hambrick's research underscores the significance of CEO succession and its potential to bring positive changes to the organization. Moreover, it emphasizes the role of managerial effectiveness in shaping the trajectory of the firm and underscores the impact of managerial efficiency.

Coach changes and CEO dismissals are well-researched topics. Much of the research on coaches is based on the idea that football clubs can serve as proxies for real-world scenarios, allowing the testing of labour economic theories. An example of this is the impact of the coach and the reasons for firing the coach (Kahn, 2000). Specifically, Kahn (2000) claims that the wider availability of data helps bridge the gap between labour theory and real-world experiments. The paper demonstrates that this holds true for various theories on monopsony power and the relationship between compensation and incentives. Additionally, Szymanski (2003) elaborates that sports-based research has experienced a significant increase in demand, partly driven by academic reasons, as sports provide numerous natural experiments for labour market theories. Papers by Braendle and Wirl (2005) and Mixon, Byrd and Wright (2013) directly compare football team head coaches to CEOs, examining Austrian football coach dismissals and American Football Head Coach pay, respectively, in relation to CEOs.

Further similarities between coaches and CEOs are highlighted in other papers that utilize football data to test management theories. For instance, Pieper and Franck (2014) find that coaches and CEOs share similarities in media skills, accountability to a large number of stakeholders, and stress resistance. Additionally, Bryson, Buraimo, Farnell and Simmons (2021) draws comparisons between the recruitment and team selection tasks of coaches and CEOs.

Football coaches often face dismissals, and numerous studies have been conducted to identify the determinants behind these dismissals. The determinants are generally team performance, individual characteristics, or a combination of these factors

For instance, Frick, Barros and Prinz (2010) analysed 115 head coach dismissals in the German Bundesliga between 1981 and 2003. They applied a mixed logit model to examine the determinants. The main advantage of their method is the ability to combine statistical distributions in the error terms and incorporate random non-observed variables. For instance, besides the team's position and recent match results, the model can incorporate hidden variables such as internal team dynamics, boardroom politics, or external pressures from stakeholders. By accounting for these factors, the mixed logit model provides a more comprehensive understanding of the determinants driving coach dismissals.

Yet, in the results, Frick et al. compared the standard logit model against the mixed logit model and found similar outcomes. Although the mixed logit model exhibited higher significance, it did not significantly affect the overall results. The most significant factors were the team's position, time, and a dummy variable indicating if the team had lost the last three matches. The order of significance remained consistent regardless of the estimation method. The key findings indicated that losing three consecutive matches significantly increased the probability of a coach quitting. Additionally, coaches with successful track records were less likely to be fired, while coaches earning significantly above the season's average were more likely to be dismissed.

The Bundesliga is also utilized by Pieper and Franck (2014) to examine managerial dismissals. In their paper, they highlight the challenge of tracking top manager performance in real world situations, as CEOs can influence analyst forecasts and investor decisions, leading to endogeneity issues. To overcome this problem, the authors employ betting odds from a professional fixed-odds bookmaker in the German Bundesliga. By using these odds, they can recreate analyst estimates and measure their effects for involuntary coach changes in German football. One notable advantage of this approach is that none of the information can be influenced directly by the coaches themselves, who can only impact the individual team's performance. Using data from the 1998-1999 up to the 2007–2008 seasons, the study comprises 6,120 observations across 3,060 matches. Out of the total 104 coach changes, 67 were identified as involuntary and in-season. These cases were regressed using a fixed effects linear probability model (LPM), which differs from the logit model utilized by Frick et al. (2010). While the LPM assumes a linear relationship between the predictors and the dependent variable, the logit model employs a non-linear logistic transformation to estimate the probabilities of the outcomes. In all estimates of the LPM and a fixed effects logit model both league position and total points in the last 5 matches were negative and significant at 1%. Additionally, in their random effects model, the authors found that the bookmaker's expected total points in the last five matches had a positive and significant impact at the 1% level. These findings suggest that good performance decreases the likelihood of involuntary dismissals. However, when adjusting for performance, high expectations may increase the probability of dismissal.

The paper by Tena and Forrest (2007) analyses dismissals in Spain. For their 20 within-season dismissals they find that dismissals are more likely to occur when the teams are at risk of relegation. This is logical as getting demoted significantly impacts the team's financial situation and earning capacity. The authors argue that unlike in management literature, there is no ambiguity in measuring the impact of coach dismissals on performance, suggesting that assessing performance improvements becomes clearer. To investigate the causes of managerial changes, Tena and Forrest (2007) employ an ordered probit model with 2,220 observations. The model included match numbers, relegation dummies, prior game loss dummies, prior dismissal dummies, and measures of managerial efficiency. The latter refers to the degree to which the team's ranking is above or below its budget rank. Both the match number, loss dummy, and relegation zone dummy were significant and positive. The prior dismissal dummy was significantly negative, as expected, suggesting that teams are less likely to fire their coach if they already did so in the season. Despite this not all coefficients were significant with the author-provided reason that there were too little dismissals in the dataset at less than 1% of the total observations. Assuming based on their findings that relegation risk is the most important factor, Tena and Forrest (2007) examine the short-term accumulation of points as the main performance increase desired by team owners. In their model, they find that a modest increase in short-term performance. However, this occurs only at the home matches of the team and not the away matches.

On the other hand, when considering the effects of coach changes or dismissals on the team, contrasting results are found. Dobson and Goddard (2001) find negative effects on team performance over the next three months following a managerial change. They find this result based on 614 dismissals in the UK's league using an ordered probit regression model. To control for mean-reversion they deploy a combination of win-ratio variables and recent match results, explaining that despite their correlation the recent win variables must be more erratic than the win-ratio variables. The test for a statistical difference then shows there is no significant mean reversion. However, note that this method is less robust than other papers. Based on the negative effects on performance Dobson and Goddard (2001) state that the large amount of in-season dismissals would appear counterproductive. However, they first try to explain this by proposing that team owners are willing to sacrifice the remainder of the season in exchange for long-term gains in future seasons. Yet, later they also acknowledge that these findings do not apply to dismissals driven by short-term pressures, and they speculate that team owners may resort to dismissing coaches as a frantic effort to avoid losses or demotion. Given the increase in variance, they argue that after a dismissal, team performance may either improve significantly or deteriorate more, with the latter having minimal impact on the final outcome.

Contrastingly, Bruinshoofd and ter Weel (2003) found that there is an increase in performance after dismissing the coach. However, this increase in performance is also observed in their control group. Interestingly, based on the control group results, it is suggested that the performance would have increased even more rapidly if the manager had not been forced to resign. In their study, Bruinshoofd and ter Weel analysed data from 27 coach dismissals in the Dutch top division between 1988 and 2000, using the number of points as a proxy for team performance. To find the control group they look at performance loss. The drop in performance for dismissals corresponds to a decrease from 95% to 65% of the season's average. This finding is used to set three requirements for the control group. Namely, initial performance is less than 10% above average, a decline of 25% in 4 games, and a performance of at most 65% of the season's average after 4 games. Note that this method of selecting the control group does not result in matched dismissals as the control group of 103 is significantly larger. This method in selecting the control group may be suboptimal as not matching 1-to-1 might create too inclusive groups.

The paper by Ter Weel (2011) stands out as the only study that directly compares and explains the results of various studies on managerial turnover and company performance using Dutch football data. In the paper (Ter Weel, 2011) compares CEO studies against football-based results. Although he does not define a specific model for the manager data, the author concludes that comparisons can be made and theories can be explained using football when it comes to actual manager performance. For the football based analysis they utilize difference-in-difference and 2SLS estimates, which differ from the regular regressions used in most other papers. The selection method for the control group is similar to that of Bruinshoofd and ter Weel (2003), as are the results, reaching the same conclusions regarding the Dutch league, namely, no increase in performance after a dismissal.

Koning (2003) also conducted a study on the Dutch Eredivisie, focusing on goal differences as a proxy for performance. The author analysed 28 coach dismissals that occurred between 1993 and 1998 and found no significant change in performance following a coach dismissal. Based on this, the paper argues that dismissals occur too often and ascribes it to media and fan pressure instead of performance. The paper is unique as it makes a clear distinction between defensive and offensive performance changes, noting that the defensive skills increase as a new coach takes over. The author argues that this might indicate that the new coach is more concerned about not losing than winning and prefers less aggressive strategies. One of the challenges highlighted in the paper is the issue of comparing the performance of the new coach with that of the previous coach, as they will never have the same opponents. To address this problem, the author used goal differences as a measure. However, this approach only partially resolves the issue. Furthermore, the study also revealed a significant difference between home and away performance, indicating that the number of goals scored alone may not be a reliable indicator of team performance.

Balduck, Buelens and Philippaerts (2010) conducted a study on coach dismissals in Belgium between 1998 and 2003. The study examined 72 dismissals and found no significant effect on team performance, measured in terms of points, as a result of a coach change. The authors employed a control group to differentiate between the effects of regression to the mean and the actual impact of coach changes on performance. Their approach was inspired by the methodology used in Bruinshoofd and ter Weel (2003) and involved selecting a control group based on the prior eight weeks.

The analysis of the Dutch Eredivisie in this paper builds upon the research conducted by Van Ours and Van Tuijl (2016). The dataset used in their study covers the period from 2000 to 2014 and includes a total of 59 coach changes, of which 42 were dismissals. Van Ours and Van Tuijl addresses the challenge of selecting an appropriate control group by utilizing third-party data in the form of bookmaker odds. This approach enables the 1-to-1 matching of each actual observation with a suitable counterfactual observation. With this, eliminating some of the control group selection issues found in Bruinshoofd and ter Weel (2003), improving on the control method of Dobson and Goddard (2001), and including an opponent dummy to account for the issues described by Koning (2003). Moreover, Van Ours and Van Tuijl addresses the concerns raised by Koning (2003) regarding the comparability of performance by considering multiple indicators, including points, wins, and goal differences, when tracking team performance following coach changes. By examining these various metrics, the study aims to provide a more comprehensive assessment of the impact of coach changes on team performance.

For CEO data, there has been scepticism regarding the direct influence of CEOs on a firm's performance due to the multitude of individuals involved. However, M. F. Wiersema (1995) demonstrates that CEOs indeed possess the power to shape the trajectory of a company. In cases where there is a sudden "non-routine" succession of CEO he finds there is a more divestment or exiting compared to situations where the status quo is maintained. Moreover, these firms tend to downsize their core business and experience lower growth compared to firms that do not undergo such restructuring. This indicates that management teams can impact firm performance by establishing a stable governance structure. Yet, without the aggressive restructuring of the new CEO, the firm's performance may have ultimately been worse as the core business of the company may have been in a dying market. In other words, the study reveals that new executives often break away from past strategic decisions and undertake a complete reassessment of the firm's strategy. It should be considered that the hiring of these new executives may have been motivated by the need to redevelop the firm's strategy, given the involuntary departure of their predecessors. Overall, the paper provides evidence of a direct association between CEO dismissals and subsequent firm performance.

CEO departures not only impact the organizational structure of a firm, but also have implications for shareholder wealth. In the context of UK firms from 1990 to 1995, Dedman and Lin (2002) demonstrate that there is a negative market reaction to CEO departures, particularly when the departures are the result of dismissals or if the CEOs have found better opportunities elsewhere. The study employs a three-day event window following the dismissal to estimate this reaction. Furthermore, the research reveals that firms opting not to announce the departure of their CEO experience poorer performance compared to firms that choose to disclose such information. Interestingly, firms that announce a replacement at the same time as the change have almost no market reaction. These findings indicate that stock markets are indeed influenced by CEO changes and that the manner of communication regarding the departure plays a role in shaping market perceptions. While the three-day event window may be relatively short for the purposes of my analysis, the study also highlights that firms tend to observe an increase in their return on assets two years after the CEO departure. This suggests that the effects of CEO departures on firm performance extend beyond the immediate reaction and may manifest in improved financial performance over a longer time horizon.

Stock prices can exhibit significant movements before a CEO change, indicating that the dismissal may be influenced by poor stock performance. However, Ertugrul and Krishnan (2011) find that nearly half (49%) of the firms that dismiss their CEOs do not experience negative excess returns in the months leading up to the dismissal, and 37% do not even have negative returns. Their study examines CEO turnover between 1996 and 2008 and identifies two primary reasons why boards dismiss CEOs without negative (excess) stock returns. The first reason is associated with company-wide corporate scandals or other unethical and illegal actions by the CEO. In such cases, the board may choose to dismiss the CEO to address the negative repercussions of these actions. The second reason involves proactive boards that dismiss CEOs with low abilities before they can harm the company. The effectiveness of this approach is enhanced when directors and board members have increased equity-based compensation, aligning their interests with those of the shareholders. Notably, Ertugrul and Krishnan (2011) did not find supporting evidence for three other hypotheses: shareholder intervention due to dissatisfaction with low or no firm value increases, differences in opinion between the CEO and the board regarding strategic direction, and personal disagreements between the CEO and the board unrelated to the firm.

Furthermore, the study reveals that both early and late CEO dismissals are preceded by a decrease in performance, followed by subsequent improvements in operating performance. In the case of early dismissals, there is initially a short dip in performance after the removal of the incumbent CEO before shareholders benefit overall in the next year, which is consistent with the idea of the previous CEO being a low ability CEO.

It is evident that poor stock performance alone cannot account for the increasing frequency of involuntary CEO exits over time. According to Farrell and Whidbee (2003), it is not merely poor performance, but rather the deviation from expected performance that raises the likelihood of CEO dismissal. The study reveals an inverse relationship between the one-year analyst forecast error and the probability of CEO dismissal. In other words, a negative forecast error or underperformance increases the likelihood of dismissal. Dismissal probability further increases when analysts agree on the poor outlook, implying a lower variance or dispersion in forecasts increases the probability. Moreover, Farrell and Whidbee (2003) find that when the five-year earnings-per-share (EPS) outlook is very low, the board is inclined to hire a more radical replacement with different strategic perspectives.

Supporting this perspective, M. Wiersema and Zhang (2011) acknowledge the influence of analysts on shaping the board's opinion regarding CEO replacement. They argue that firm performance alone is insufficient as a criterion because it can be affected by various external factors, making it challenging for the board to accurately assess the CEO's performance and capabilities. However, analysts are deemed as prominent information intermediaries, by M. Wiersema and Zhang (2011), and considered qualified in evaluating firm and leadership performance by Wiesenfeld, Wurthmann and Hambrick (2008). Even if these qualified assessors do not provide new information to the board, the board is still incentivized to listen to their opinions because analysts hold sway over investors, whom the board must also consider. In contrast to Pieper and Franck (2014), the paper does not consider CEO influence on analysts as a major problem. It does mention that analysts are susceptible to herd behaviour and are biased upwards in their estimates. Both are, however, not considered problematic for this study's application of analyst estimates.

Lastly, also Fredrickson, Hambrick and Baumrin (1988) support the notion that organizational performance has an impact on the dismissal rate of CEOs. However, the relationship between organizational performance and CEO dismissal is not a direct one according to them. Fredrickson et al. suggest that the effect of organizational performance on CEO dismissal is mediated by various factors, including the board's expectations, the availability of alternatives, the level of influence held by the incumbent CEO, and the values of the board. Taking M. Wiersema and Zhang (2011) their view on expectations being influenced by analysts, we can argue that the main determinants are unobserved apart from board expectations, proxied by analyst estimates.

3 Data

This paper will utilize data on both stock market companies and data on the top professional football league of the Netherlands, called the Eredivisie. The football data was collected by Van Ours and Van Tuijl (2016), who collected statistics on coach dismissals and quits from various internet sources for their own paper. Note that the dataset has a total of 59 coach change observations and 42 coach dismissals, see Table 7 in the Appendix for an overview.

The Eredivisie data stretches from the 2000-2001 season to the 2013-2014 season and includes 27 different clubs. For each season Van Ours and Van Tuijl collected points, wins, bookmaker odds[1], game location, team rank, and individual coach statistics. The bookmaker odds are largely retrieved from William Hill (97%) with the remainder coming from Ladbrokers (2%) and Gamebookers (1%).

The descriptive statistics in Table 1 show a general overview of the 8568 data points and the

[1]The two matches without bookmaker data have an assumed cumulative surprise of 0.

subsection of 1428 observations consisting of seasons with a coach dismissal. Cumulative surprise refers to the difference between expected results and achieved results and cumulative points is the sum of points up to the respective match. Notably, it can be found that the cumulative surprise in the dismissal seasons tends to be more negative, with the average cumulative surprise of dismissals at -3.42 compared to the entire dataset at 0.09. Cumulative surprise indicates the team's performance relative to expectations. Based on this, the negative cumulative surprise shows the team is underperforming and might be an indicator to remove the coach. Moreover, the mean rank is equal to 9.51 and 9.47 which is due to a different number of teams being promoted in various years. Note that the age variable does not differ significantly for the subset, while the National Team parameter does decrease, suggesting dismissed coaches are less likely to have played on the national team. The means of the points and wins variables are both smaller in the dismissal subset, going from 1.38 to 1.08 and 0.38 to 0.29, respectively. Based on this, dismissal season teams are winning 10% less of the games than non-dismissal season teams. The last performance metric, cumulative points, is also lower for the dismissal subset, which is normal as the average Points also decreases, ending at 18.06, a whole 6+ points lower on average than the complete sample.

Table 1: Descriptive Statistics for Football Variables Used in the Analysis

	All Observations			**Dismissal seasons**		
	Mean	**Minimum**	**Maximum**	**Mean**	**Minimum**	**Maximum**
Home Game	0.5	0	1	0.5	0	1
Age Coach	46.89	31	66	46.84	33	66
National Team	0.39	0	1	0.24	0	1
Points	1.38	0	3	1.08	0	3
Wins	0.38	0	1	0.29	0	1
Position opponent	9.57	1	18	9.47	1	18
CumSurp	0.09	-18.31	19.49	-3.42	-17.41	10.28
CumPoints	24.21	0	87	18.06	0	73

Note: Data is based on the Van Ours and Van Tuijl (2016) dataset. Split into all available observations (8568) and all dismissal season observations (1428).

Next to the coach data, a comparable dataset for CEO dismissals and changes is used. The data was retrieved by Gentry and Boivie (2021) and includes 7398 CEO changes of which 1414 are dismissals over the period January 1992 to December 2018. Based on the descriptions given only the dismissals classified as involuntary due to poor performance and involuntary due to personal issues are considered. The latter referring to either breaking the law or the companies own policies. Next to dismissals the dataset also include voluntary retirement, resignation due to new opportunities, and other non-dismissal related changes. This dataset only includes the CEO change identifiers, dates, and company keys, hence additional datasets are needed for the related stock market performance and surprise metrics.

For stock market data, the Center for Research in Security Prices (CRSP) is utilized. The retrieved dataset covers the period of 01-01-1990 to 31-12-2020 which extends two years beyond the CEO data. This ensures that the effects can be captured for all observations in the CEO dataset. The CRSP dataset consists of information on the monthly return and the monthly value weighted index return for all the companies in the CEO dataset.

For the surprise metric, the earnings per share forecast of individual companies is downloaded from I/B/E/S. The data again covers the periods January 1990 to December 2020 to ensure that all CEO data can be used. Earnings per Share data is downloaded for all forecast periods along with its actual value, forecast announcement date, and earnings date. The latest forecast from each analyst at the relevant point in time is selected as the expectation, while prior forecasts from the same analyst are discarded. The cumulative surprise based on analyst estimates is then calculated, following a similar approach as the bookmaker-based cumulative surprise described by Van Ours and Van Tuijl (2016).

Note that these datasets all come with different identifiers and that they are matched based on the gvkey-CUSIP9 library provided by Wharton Research Data Services (WRDS).

As some of the datasets have missing data I cross-check against all three datasets to find a total of 3898 CEO changes of which 772 are dismissals. To ensure data quality, companies with surprise data from only one analyst are removed. Subsequently, companies are selected only if, on average, at least five out of six surprise data points are available per year during the sample period. Lastly, stocks with less than 10 years of market data are excluded to maintain a sufficiently large sample size for selecting the counterfactual.

The descriptive statistics of the CEO Data are shown in Table 2, note that the data is split for the three datasets used. For the analyst data it can be found that the mean estimate is slightly higher than the mean of the actual EPS number, this upward bias is in line with the prior research of Pieper and Franck (2014). Contrastingly, in the selected data the mean is not higher anymore, which may be due to my method of selection where I only select the most recent estimate of an analyst. This would suggest that analysts move closer towards the actual amount as the announcement closes in, having on average a very tiny end error of 0.01 in estimating the EPS. The min and max values show similar results where the later estimates appear to be better, additionally companies that were not selected or had little data are discarded, meaning less covered and unrealistic estimates are removed from the dataset.

For the monthly returns, it is observed that the companies exhibit higher average returns compared to the index. However, it should be noted that the index includes a larger number of companies than the dataset itself, which is limited to the companies in the CEO dataset. A comparison of the minimum and maximum values reveals a wider range for the companies compared to the index. This discrepancy is also reflected in the Kurtosis measure, with the index having a value of 1.55 and the companies showing a significantly higher value of 207.23, indicating a higher degree of variance in the data. However, in the selected sample, the Kurtosis decreases to 93.94, suggesting that the stocks selected based on data availability, which are typically better known or better covered, exhibit smaller and less extreme movements. An example is the exclusion of Vanda Pharmaceuticals (NASDAQ: VNDA) from the dataset, which had a remarkably high return of 1349% in one month in 2009, leading to a reduction in the maximum return from 1349.51 to 936.36.

Turning to the CEO dataset, it is observed that the dismissal rate in the full dataset is 0.19, indicating that approximately 20% of CEO changes are due to dismissals. In the selected dataset, the dismissal rate remains exactly 20%. The tenure number slightly exceeds one, suggesting that the majority of CEOs only have one tenure recorded in the dataset. Specifically, there are 90 CEOs who occur twice and 6 who occur three times, while the remaining 3802 CEOs occur only once.

Table 2: Descriptive Statistics for CEO data Used in the Analysis

	Complete Dataset				Selected Data			
	obs	**Mean**	**Min**	**Max**	**obs**	**Mean**	**Min**	**Max**
Analyst Data								
Analyst EPS Estimate	12,449,113	1.30	-210.96	9829.86	52,301	0.74	-27.79	460.83
Actual EPS	196,554	1.24	-90.37	491.82	52,301	0.75	-46.4	194.8
Stock Data (%)								
Month Return	743,422	1.53	-98.13	1349.51	412,766	1.51	-98.13	937.36
Value-weighted Return	372	.90	-18.48	12.97	372	0.90	-18.48	12.97
CEO Data								
Dismissal	7,398	0.19	0	1	3,898	0.20	0	1
Tenure Number	7,398	1.03	1	4	3,898	1.03	0	3

Note: Descriptive statistics are shown for three separate datasets that together make up the CEO data. Note that the selection is based on cross-checking between datasets.

Figure 1 displays the cumulative surprise throughout the seasons for the different coach changes, while Figure 2 illustrates the cumulative surprise for the CEO changes. These graphs show that coach dismissals tend to result in a bias towards negative cumulative surprises, especially compared to the quits and no change data points. The kernel densities for the CEO changes exhibit more pronounced spikes due to the larger number of observations, yet there is still a noticeable left skewness, indicating a higher prevalence of negative cumulative surprises under CEO dismissals compared to no change data points. This is backed up by the mean being considerably different at -0.036 for no change and -0.185 for dismissals with all changes in the middle at -0.089. Note that no change being negative can be explained by the upward bias found in analyst expectations. Nevertheless, the negative shift based on third party estimates is in line with the football results where the cumulative surprise also decreases from 0.09 to -3.42, as discussed previously.

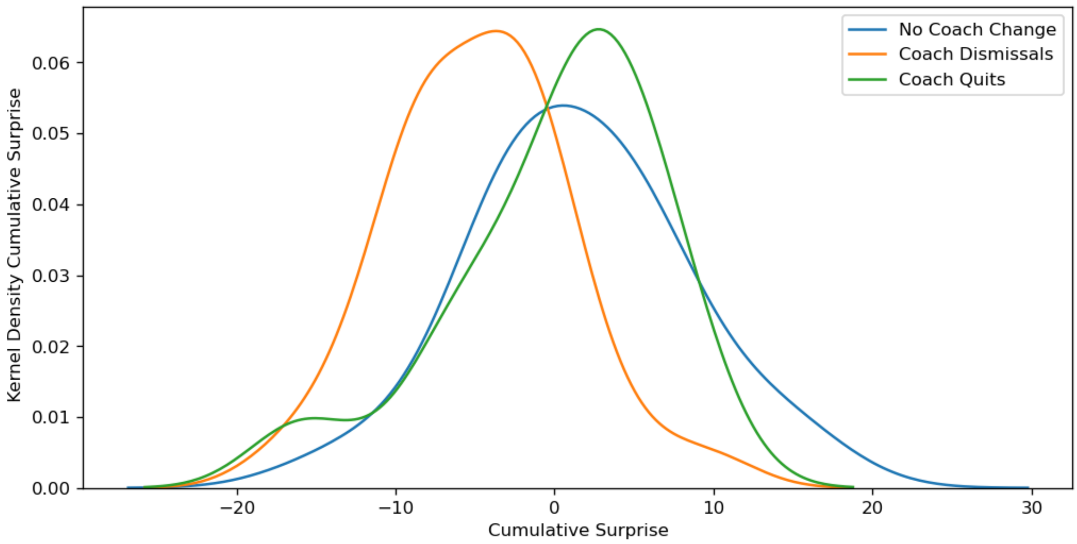

Figure 1: Cumulative surprise compared for no coach changes, coach dismissals, and coach quits. Cumulative surprise is based on the last match in the season.

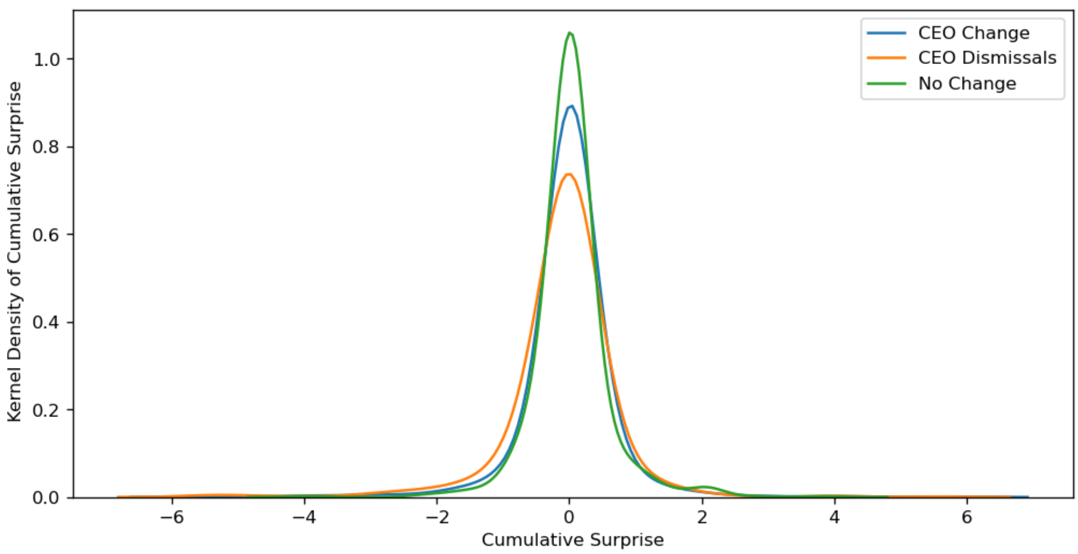

Figure 2: Cumulative surprise compared for CEO changes, CEO dismissals, and no CEO change. Cumulative surprise is based on a 9-month period, assuming the change occurs in the sixth month.

4 Methodology

The methodology consists of three main sections. In the first section, I describe the general variables and data used throughout the study. These serve as the foundation for the subsequent sections. The second section presents methods to analyse the reasons for CEO and Coach dismissal, while the third section examines the effects of dismissal or succession.

In the analysis of the stock market data, a period of 16 months into the future from the point of a CEO change and 17 months into the past is considered. This way each dismissal or change event has the same number of observations as the football seasons.

Using the monthly data and the index returns excess returns are estimated using the formula in equation 1 which compares the stock against the value weighted index and finds an alpha and beta estimate. The excess return is the difference between the estimated return based on the market and the actual return. Hence, it is cleaned from market-wide movements and expectations and is significantly more firm specific.

$$
\begin{aligned}
re_{i,t} &= r_{i,t} - \hat{r_{i,t}} \\
\hat{r}_{i,t} &= \alpha + \beta * r_{vw,t}
\end{aligned}
\tag{1}
$$

After calculating the excess return also the cumulative return and cumulative excess return are calculated as shown in Equation 2. The cumulative number is calculated as the product of the last k months of (excess) returns.

$$
\begin{aligned}
CumReturnLast_{i,k} &= \prod_{j}^{k} (1 + r_{i,(t-j)}) - 1 \\
CumExcessReturnLast_{i,k} &= \prod_{j}^{k} (1 + re_{i,(t-j)}) - 1
\end{aligned}
\tag{2}
$$

Next to these statistics, the cumulative surprise is also needed. The cumulative surprise in the CEO scenario is calculated as the difference between the expected analyst forecast for the EPS and the realized analyst forecast for the EPS. This is done by selecting the closest analyst forecast to the point of departure, which can also be just after the departure, and the 3 data points before. For each point, the average of the analyst estimates is calculated to derive the mean expectation, which is then contrasted with the actual EPS value to obtain a surprise value. The cumulative surprise is obtained by summing these surprises across the relevant meetings.

For the coach data, the calculation of cumulative surprise follows the method introduced by Van Ours and Van Tuijl (2016). In this case, third-party estimates in the form of bookmaker odds are utilized. These odds are used to derive an expectation, which is subsequently compared to the actual results. Equation 3 illustrates this calculation, where three points are assigned for a win, one point for a draw, and zero points for a loss. The expectation is based on the probabilities defined by the odds, taking into account the division by the sum of the odds to adjust for bookmaker's premiums.

$$
\begin{aligned}
Surprise_i &= (3\mathbb{1}_{win,i} + \mathbb{1}_{draw,i} + 0 * \mathbb{1}_{loss,i}) - (3P_{win,i} + P_{draw,i} + 0 * P_{loss,i}) \\
P_{win,i} &= \frac{100/Odd_{win,i}}{Odd_{win,i} + Odd_{draw,i} + Odd_{loss,i}} \\
P_{draw,i} &= \frac{100/Odd_{draw,i}}{Odd_{win,i} + Odd_{draw,i} + Odd_{loss,i}} \\
P_{loss,i} &= \frac{100/Odd_{loss,i}}{Odd_{win,i} + Odd_{draw,i} + Odd_{loss,i}}
\end{aligned}
\tag{3}
$$

Besides creating the cumulative surprise I also define the Cumulative Points, the sum of all points up to that point in the season, and the coach's experience defined as the cumulative sum of matches, across clubs, up to that point for the coach. Note that the experience statistic is subject to left-censoring as there is no data in the dataset prior to 2000. Thus, all coaches start with 0 years of experience in the Eredivisie in the beginning of the dataset. Nevertheless, this is not a significant issue for the chosen estimation method, the logit model.

4.1 Relation Between Performance and Dismissal

To bring further insight into the causes for dismissal for both CEOs and Coaches I estimate three logit models. The logit regressions are then used to quantify the impact of various variables on dismissal likelihood for both groups. Equation 4 shows the regression models, selected from general to specific. For this only changes that occur between game 5 and 34 are included as coach changes.

$$
\begin{aligned}
Dismissal_{i,t,CEO} &= \alpha + \beta_1 * r_{l3,i,t-1} + \beta_2 * re_{l3,i,t} + \beta_3 * CS_{i,t-1} \\
Dismissal_{i,j,k,Coach} &= \eta_i + \beta_1 * WNR_{i,j,k} + \beta_2 * AGE_{i,j,k} + \beta_3 * EXP_{i,j,k} \\
&\quad + \beta_4 * Win_{i,j-1,k} + \beta_5 * Points_{l4,i,j,k} + \beta_6 * CS_{i,j-1,k} \\
Dismissal_{i,j,k,Coach} &= \eta_i + \beta_1 * EXP_{i,j,k} + \beta_2 * Points_{l4,i,j,k} + \beta_3 * CS_{i,j-1,k}
\end{aligned}
\tag{4}
$$

The first equation presents the logit regression model for the CEO data, where the dependent variable is equal to 1 if a dismissal or change occurs, and 0 otherwise. The model further has a constant, the last 3 months returns excluding the current month, the last 3 months of excess market returns including the current month, and the cumulative surprise as described above as explanatory variables. Furthermore, i refers to the company and t refers to the month in question with $t-1$ being the prior month and indexes $l3$ being the "last 3" months. For all dismissal or CEO change moments the prior 16 months are included. This means that each event has 17 data points. This yields a total of 101,705 data points used for dismissals and 62,487 for all changes.

It is important to note that the dismissal data includes more observations than the all changes data. This is because for dismissals, all data points after the dismissal event are discarded, while for all changes, all data points after the change event are discarded as well. By discarding post-event data only if we are looking at the event, we ensure that the analysis focuses on the relevant information and maximize our data. The logit regression makes use of white standard errors to account for differences between companies.

The second logit regression is for the coach data and includes a dependent variable equal to 1 if a dismissal or change occurs in a match, and 0 for all other matches. Due to the smaller number of observations team fixed effects are used, represented by η_i. Additionally, the regression has the match number, coach age, and coach experience as control variables next to the performance metrics. These being the $Win_{i,j-1,k}$ variable which symbolises a win in the prior match, the $Points_{l4,i,j,k}$ variable which refers to the points scored in the last 4 matches and the $CS_{i,j-1,k}$ variable. The CS, or cumulative surprise, is defined as described above for the coach changes. Note that the index is not based on time t as in the CEO model but uses match j and season k, while still identifying club i. The third model is a shortened model for coach dismissal based on the second, it was selected to help in drawing parallels across the datasets. While the variables do not match exactly they serve to compare returns against points and relate the CS variable to the other CEO CS variable. Both coach models again use robust standard errors to deal with the heteroscedasticity caused by different teams. The Coach model is estimated for all observations up to and including the dismissal. This means that we use all data apart from observations after a dismissal or coach change has occurred for that specific season[2], yielding us 6,861 observations for dismissals and 6,560 observations for all changes.

To check for potential selection biases we also use random oversampling, through the imblearn package in Python. This is based on Ustyannie and Suprapto (2020), who suggest that oversampling can help in imbalanced datasets, and Mohammed, Rawashdeh and Abdullah (2020), who suggest that oversampling works better than undersampling. Note that there is no resampling based on the dependent variable as prediction of the dependent variable itself is not the main focus of the model. All clubs have the same number of observations by resampling the minority groups. While accounting for bias of teams being underrepresented, this does overstate the importance of single observations for teams such as "Cambuur Leeuwarden", who are resampled significantly. After resampling there are 11,340 observations for dismissals and 10,908 observations for all changes.

4.2 Relation Between Dismissal and Better Performance

The effects of dismissals and changes are estimated using regression, for the Eredivisie data fixed effects are used based on the club and season combination. This is especially important because all the regressions are within season, hence within-season effects are needed. Contrastingly, for the CEO data no fixed effects are used on account of the number of companies considered being too large. While this slims the comparison in method, the results should not be significantly affected as the much larger number of CEO data points allows for reliable estimates of the coefficients, without the need to filter out all individual company effects.

4.2.1 Coach Changes

The fixed effect regression for the coach data is shown in Equation 5 and only uses data from selected seasons. Meaning that for the dismissal regression only the seasons with a dismissal are included. All the (fixed) regressions are estimated using the Statsmodels package. The following equation shows the performance metric y_{ijk} being regressed which is one of the three metrics, namely Points, Win, and Goal Difference, for club i playing match j in season k.

$$y_{ijk} = \eta_{ik} + r'_{ijk}\beta + \delta d_{ijk} + \varepsilon_{ijk} \tag{5}$$

As can be seen in the equation η_{ik} is the fixed effects constant for the i-th club in the k-th season. Vector r consists of the game location[3] and the rank of the opposing team[4], both are included to limit the bias from outside influences, as found by Bruinshoofd and ter Weel (2003) for home advantage and Koning (2003) for opponent bias. Lastly, the dummy variable d_{ijk} that is 1 when a coach change or dismissal occurs and 0 else is included.

[2]If there is a coach dismissal (change) in game 20 all observations 1-20 are included. Similarly, if there is no coach dismissal (change) or if it occurs in game 34 the complete season is included.

[3]Whether the game is an away or home game significantly affects the performance of the team

[4]All teams are ranked based on their prior season performance, with the promoted team receiving the rank 18

To accurately test whether the results are due to the coach change a control group needs to be considered. For this every coach dismissal or change is, if possible, matched to a similar moment where no change or dismissal occurs. The results are then compared to find if there is a real change in performance as a result of the coach change.

To find the counterfactual I use two different methods. The first method is based on the approach used in Van Ours and Van Tuijl (2016). It involves selecting a similar moment in another season for the same club based on the cumulative surprise (CS_a) in the match prior to the coach change. Specifically, Van Ours and Van Tuijl order the cumulative surprises of non-change seasons and choose the observation (CS_c) that is below the actual coach change's last match if $CS_c - CS_a < 0.5$.

The second method also relies on the CS value but incorporates a modification[5]. It aims to minimize the distance in both directions, allowing for the selection of an observation above the actual change if it is closer than the one below. This method provides flexibility in choosing the closest match based on CS values.

Using the selected counterfactuals the regression shown in Equation 6 is estimated. Note that I include both the actual changes as well as the counterfactual changes by means of two dummies, namely d_{ijk} and C_{ijk}. Because of this only seasons with actual matches, which means a counterfactual exists, and seasons with a counterfactual in it are included. The remainder of the regression is the same as before.

$$y_{ijk} = \eta_{ik} + r'_{ijk}\beta + \delta d_{ijk} + \gamma * C_{ijk} + \varepsilon_{ijk} \tag{6}$$

4.2.2 CEO Changes

Our estimation method for assessing the impact of CEO changes is similar to that of the coaches. However, it is not a fixed effects regression model due to the large variety of companies included in the data. Equation 7 shows two specifications of the model presented in the results. The first one regresses the returns of the last month and the second one regresses the forward-looking returns of the next 3 months, this is to smooth out potential one month interference. Both are regressed on a constant, the last month value-weighted index return, the coming three months of index return, the last three months of index return, excess return over the last month, and excess return over the prior month.

$$\begin{aligned} r_{i,t} &= \alpha + \beta_1 r_{f3,vw,t} + \beta_2 r_{vw,t} + \beta_3 r_{vw,t-1} + \beta_4 re_{i,t-1} + \beta_5 re_{i,t} + \delta d_{i,t} + \varepsilon_{i,t} \\ re_{f3,i,t} &= \alpha + \beta_1 r_{f3,vw,t} + \beta_2 r_{vw,t} + \beta_3 r_{vw,t-1} + \beta_4 re_{i,t-1} + \beta_5 re_{i,t} + \delta d_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

In order to form a control group for CEO changes, counterfactuals are needed, similar to coach changes. The cumulative surprise is used as a measure, but since it is less specific for companies, an additional method is considered to help find suitable counterfactuals. The counterfactual is then found by minimizing the distance between the potential counterfactuals and the actual CEO change for different variables.

[5]The difference between the methods is illustrated by the example of finding the closest number to 5 in the series: 1 3 4 5 7 10. The first method would have selected 7 because it is the next number when sorting, the second method would have selected 4 because it is the closest number to 5.

$$
\begin{aligned}
idx_{C-1} &= argmin_t \; CS_{i,t-1} - CS_{i,A-1} \\
idx_{C-1} &= argmin_t \left(\sqrt{\left(CS_{i,t-1} - CS_{i,A-1}\right)^2 + \left(re_{l3,i,t-1} - re_{l3,i,A-1}\right)^2} \right)
\end{aligned} \tag{8}
$$

Equation 8 presents the methodology for selecting the control group based on the cumulative surprise and the cumulative surprise and excess return combination. To do so, first the actual change observation (A) is identified and the prior observation ($A-1$) is found. Then this prior observation is matched to the observation $C-1$ which is the closest match based on the distance formulas. The counterfactual observation with time index C for the company's actual dismissal at time A is the next observation after $C-1$.

Once the counterfactuals are determined, a regression analysis is conducted by including both the actual CEO changes and the counterfactual CEO changes. The regression formula used is represented by Equation 9. Note, this regression again contains the same variables as equation 7, with the addition of the counterfactual observation dummy.

$$
\begin{aligned}
r_{i,t} &= \alpha + \beta_1 r_{f3,vw,t} + \beta_2 r_{vw,t} + \beta_3 r_{vw,t-1} + \beta_4 re_{i,t-1} + \beta_5 re_{i,t} + \delta d_{i,t} + \gamma C_{i,t} + \varepsilon_{i,t} \\
re_{f3,i,t} &= \alpha + \beta_1 r_{f3,vw,t} + \beta_2 r_{vw,t} + \beta_3 r_{vw,t-1} + \beta_4 re_{i,t-1} + \beta_5 re_{i,t} + \delta d_{i,t} + \gamma C_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{9}
$$

4.2.3 Comparing Parameter Estimates

In both the CEO and coach change regressions, the analyses were conducted using a single comprehensive dataset. A multivariate Wald test is used to assess the significance of the differences between the actual and counterfactual dummies. This test uses the F-distribution and is also known as an F-test. The Wald-test, specified as in Equation 10, allows for testing the hypothesis of equality, denoted as $H_0 : \delta = \gamma$. The derivation shows the adjustment for my hypothesis, testing the single restriction (Q=1) of equality (r=0) for two parameters (P=2). Note that for both the CEO and coach change the formula is the same apart from n.

$$
\begin{aligned}
W &= \frac{\left(R\hat{\theta} - r\right)' \left[R\left(\hat{\Sigma}/n\right)R\right]^{-1} \left(R\hat{\theta} - r\right)}{Q} \sim F\left(Q, n-P\right) \\
&= \left([1,-1]\begin{bmatrix}\delta \\ \gamma\end{bmatrix}\right)' \left[[1,-1]\left(\hat{\Sigma}/n\right)\begin{bmatrix}1 \\ -1\end{bmatrix}\right]^{-1} \left([1,-1]\begin{bmatrix}\delta \\ \gamma\end{bmatrix}\right) \sim F\left(1, n-2\right) \\
&= \frac{n\left(\delta-\gamma\right)'\left(\delta-\gamma\right)}{\hat{\Sigma}_{11} - 2\hat{\Sigma}_{12} + \hat{\Sigma}_{22}} \sim F\left(1, n-2\right)
\end{aligned} \tag{10}
$$

5 Results

5.1 Dismissal Causes

Based on the available data, logit regressions were estimated to analyse the causes of dismissal for CEO and Coach changes. The results are presented in Table 3. Note that next to the base regressions also a resampled model is estimated to account for the different number of observations between clubs.

In the coach model we find three significant variables, namely AGE, CumSurp, and EXP. We find that all variables decrease the likelihood for the coach to be dismissed due to their negative sign apart from "WNR". The WNR, or game number, variable is the only one that is positive, yet it is not statistically different from 0. The main argument for inclusion is to separate coach experience from time progression.

Based on the "EXP" and "AGE" variables, I find that older and more experienced coaches are less likely to be fired or quit compared to younger, less experienced coaches. However, they are more likely to quit than be fired within their respective age and experience groups.

It is important to mention that the variables Plast4 and WinL, denoting points in the last 4 matches and winning the prior match, are not significant. However, this lack of significance may be due to a high correlation between these variables. When WinL is removed and only the Plast4 variable is considered, it becomes significant. This can be observed in the Base Model, where it achieves a t-statistic of -4.33, making it significant at the 1% level. Nonetheless, the insignificance of the last game may indicate that team owners prioritize longer streaks of performance rather than being influenced by a single bad game. This aligns with the findings of Frick et al. (2010), who reported the significance of the last three game wins, particularly for quits. Our proxy for this, points in the last 4 matches, also shows similar patterns.

The points variable is significant at 10% in the extended model for all changes, possibly, indicating that individual coaches are more likely to resign in-season following poor recent absolute performance. On the other hand, coaches are more likely to be fired when their team's relative performance is poor, as evidenced by the significance and size of the "CumSurp" coefficient in the full model. All in the significance of the CumSurp variable underlines that team owners consider the team's performance relative to mass expectations, which is logical as underperforming expectations implies both poor performance and disappointment among fans.

For the resampled models the coefficients remain largely similar in the full model, apart from the points in the last 4 matches, which becomes much smaller and the WinL variable which becomes larger. The resampled data introduces a slight bias towards seasons of low-ranked teams, which were underrepresented in the main dataset. This difference might suggest that bottom-ranked teams have less patient management, choosing to fire coaches after a bad results rather than a prolonged string of poor performance. Nevertheless, the resampled data underlines the previous results and shows that there is no further significant differences between teams.

Table 3: Results of logit regressions for the full and baseline coach models and the CEO model

	Dismissals		All Changes	
	Base model	**Resampled Model**	**Base Model**	**Resampled Model**
Full Model Coaches				
WNR	0.015 (0.42)	0.203 (6.17)***	0.056 (1.19)	0.127 (3.46)***
AGE	-0.045 (-3.49)***	-0.087 (-5.83)***	-0.021 (-1.95)*	-0.044 (-4.75)***
WinL	-0.886 (-1.61)	-1.488 (-3.02)***	-0.412 (-1.07)	-1.215 (-3.55)***
CumSurp	-0.219 (-3.36)***	-0.279 (-4.12)***	-0.159 (-3.07)***	-0.191 (-5.00)***
EXP	-0.110 (-2.18)**	-0.283 (-4.84)***	-0.116 (-2.16)**	-0.133 (-3.01)***
Plast4	-0.117 (-1.18)	-0.048 (-0.52)	-0.125 (-1.89)*	-0.019 (-0.39)
N	6,861	11,340	6,560	10,908
Base Model Coaches				
CumSurp	-0.146 (-2.36)**	-0.368 (-7.45)***	-0.189 (-3.37)***	-0.297 (-6.95)***
EXP	-0.119 (-2.75)***	-0.248 (-4.96)***	-0.101 (-2.88)***	-0.101 (-3.48)***
Plast4	-0.333 (-4.33)***	-0.088 (-1.93)*	-0.173 (-2.78)***	-0.063 (-1.41)
N	6,861	11,340	6,560	10,908
Model CEOs				
cumRetLast3shift	-0.729 (-2.52)**		0.155 (1.71)*	
cumSurp3	-0.043 (-3.43)***		-0.028 (-1.96)*	
cumExRetLast3	-1.688 (-4.97)***		-0.250 (-2.23)**	
N	101,705		62,487	

Notes: Logit models are estimated using robust White standard errors without clustering. Next to club fixed effects, the coach model includes variables: WNR (match number), AGE (coach's age), WinLast (dummy variable for previous match win), CumSurprise (cumulative surprise), EXP (number of matches coached), and Plast4 (points in last four matches). The CEO model includes variables: CumReturn (return of previous three months), CumSurprise (cumulative surprise over three quarters), and CumExReturn (cumulative excess return relative to CRSP index).
*** (**) indicates significance at 1% (5%)

CEO results show similar findings, indicating that the cumulative return and excess cumulative return have negative and significant coefficients. This suggests that CEOs are more likely to be fired if the stock underperforms the market or the company's own expectations. The negative coefficient for cumulative surprise suggests that underperforming relative to analysts' expectations increases the risk of CEO dismissal. This aligns with the findings of previous research by Farrell and Whidbee (2003), highlighting the importance of analyst estimates in CEO evaluation.

Interestingly, the return coefficient for all changes is positive but only significant at 10%, implying that CEOs are more likely to leave if the firm performs exceptionally well. This may suggest that CEOs are more prone to being recruited by other companies when their current firm experiences significant success.

Furthermore, some of the lower significance can be attributed to the much smaller dataset as significant amounts of data are excluded in the all changes model. Yet, the parameter estimates are also much smaller suggesting that retirements, and other non-forced CEO changes are less likely to be caused by the market, performance, or expectations of third parties.

Comparing the variables, it is evident that prior performance measures play a significant role in explaining both coach and CEO dismissals. Coach dismissals are associated with the points achieved in the last four matches (Plast4), while CEO dismissals are influenced by cumulative return. Additionally, both the coach and CEO models demonstrate the influence of third-party estimates, with bookmaker odds for coaches and analyst estimates for CEOs. The coach model also highlights the significance of experience, which aligns with previous research.

5.2 Impact of Dismissals on Performance

To evaluate the effects of dismissals on team and company performance, two models are employed: a naive model and a matched treatment model. Alternative counterfactual selection methods are also considered for sensitivity analysis.

Table 4 presents the estimated coefficients for the dummy variables in the coach dismissal models. The full models, including control variables, are provided in Appendix Table 8.

The actual coach changes show that there is a significant increase in performance after the dismissal of the coach in all three measured metrics of points, wins, and goal difference. The actual dismissals have even higher coefficients, increasing the expected points by 0.293, probability of winning by 0.104, and goal difference by 0.273 given there has been a dismissal prior to that point in the year. In other words, after dismissing the coach a team should score .273 more goals than its opponents extra compared to prior in the year, adjusted for opponent and home advantage. These results indicate that teams should discard their coach if they need a temporary performance boost, for example to get out of relegation risk. This is in line with the results of Tena and Forrest (2007) who found a short performance boost. Moreover, I find that there are stronger performance increases as a result of dismissal compared to that of changes, as can be seen from the size of the coefficients.

Based on the table it is evident that the actual dismissals and change variables are hugely similar to the matched actual changes and dismissals. This is because the matched actual variable dummies are based on a subset of the actual change data and include only the matched pairs. Out of the total of 59 actual changes, 48 were successfully matched to a counterfactual observation based on the cumulative surprise. These 48 counterfactuals were spread across 44 different seasons, resulting in a total of 92 seasons in the regression. Similarly, for dismissals, 36 out of the 42 observations were successfully matched, yielding a total of 33 control seasons.

The matched regression analysis reveals that the control variables demonstrate similar characteristics to the actual dummies. However, it is noteworthy that the control variables exhibit reduced significance and smaller effect sizes compared to the actual dummies. This contradicts the findings of Bruinshoofd and ter Weel (2003) who said performance would have increased faster if there had been no dismissal. This difference might be attributed to the better selection of the control group through the matching process. Continuing, the F-test is used to test whether the difference between the actual and control dummies is statistically significant. The results show that the null hypothesis of similarity cannot be rejected, finding p-values between 0.40 and 0.60. Hence, it is not possible to determine that there has been a significant increase in performance resulting from the coach change. Instead, the observed performance improvement is likely attributable to mean reversion rather than the change.

Table 4: Regression Results: Effect of Coach Changes on Team Performance for Naive and Matched Regressions

	Points	**Win**	**Goal Difference**	**N**	**n**
All Coach Changes					
Actual Changes	0.253 (4.73)***	0.089 (4.52)***	0.373 (4.45)***	2006	59
Matched Actual	0.252 (4.22)***	0.095 (4.30)***	0.374 (4.00)***	3128	48
Matched Counterfactual	0.202 (2.75)***	0.067 (2.54)**	0.273 (2.37)**		44
F-test	0.60	0.42	0.50		
Coach Dismissals					
Actual Dismissals	0.293 (4.59)***	0.104 (4.49)***	0.484 (4.85)***	1428	42
Matched Actual	0.282 (4.08)***	0.103 (4.07)***	0.458 (4.21)***	2346	36
Matched Counterfactual	0.223 (2.62)***	0.070 (2.31)**	0.312 (2.33)**		33
F-test	0.59	0.41	0.40		
Sensitivity Analysis					
All Coach Changes					
Matched Actual	0.252 (4.21)***	0.095 (4.30)***	0.374 (4.00)***	3094	48
Matched Counterfactual	0.205 (2.83)***	0.067 (2.54)**	0.199 (1.70)		43
F-test	0.62	0.41	0.24		
Coach Dismissals					
Matched Actual	0.283 (4.09)***	0.103 (4.08)***	0.460 (4.23)***	2278	36
Matched Counterfactual	0.192 (2.23)**	0.054 (1.76)	0.149 (1.04)		31
F-test	0.41	0.22	0.08*		

Notes: The top section of the table includes the results for actual changes and dismissals, along with their matched variants. In the matching process, each change is matched to a counterfactual in a different season based on the cumulative surprise in the previous match. The bottom section of the table features matched results for the sensitivity analysis, which selects the counterfactual by minimizing the absolute distance. Both sections include F-tests and show the corresponding p-values for the tested hypothesis: Matched Actual = Matched Counterfactual. Note that all values are the coefficients of the dummy variables, such that actual change is the dummy representing actual changes in the data, being a 1 if any coach was changed. Similarly, Matched Counterfactual Dismissals are 1 when it is a counterfactual observation of a dismissal. N refers to the number of observations in the sample and n refers to the number of seasons considered.
*** (**) indicates significance at 1% (5%)

To further investigate the presence of mean-reversion, I use an alternative method to select counterfactuals in the control group. In the Sensitivity Analysis, the coefficients for the matched actual changes remain largely unchanged, with only slight variations due to the inclusion of fewerb seasons. Similarly, the matched counterfactual dummy coefficients exhibit minimal differences, with a slight dip observed for the goal difference variable. It is important to note that one season is lost in the matched control group and two seasons in the dismissal-only section.

The lower coefficients observed for dismissals across all three performance metrics in the sensitivity analysis may be attributed to the selection bias in the original method, where the next observation in order is chosen as the counterfactual. This implies that the selected outlook counterfactual is always slightly more positive than the actual observation. By selecting counterfactuals in both directions, I find that the performance increase in the counterfactual scenario is slightly more subdued, which is in line with picking slightly less positive counterfactuals.

Nevertheless, the F-test indicates that the null hypothesis of equality cannot be rejected, except for the goal difference variable in the matched dismissals, where it can be rejected at a significance level of 10%. Therefore, the original conclusion of mean-reversion is maintained as no significant evidence was found in support of performance increases post change. Nevertheless, it is worth noting that the actual changes may exhibit a quicker performance improvement, as indicated by their larger coefficients, but this difference is not statistically significant.

To analyse the effect of CEO dismissal on company performance, naive regressions were conducted. The results are presented in Table 5 for overall changes and Table 6 for dismissals. The tables also include the results for the two different matching approaches used for the control group. All regressions were performed on a total of 260,118 observations, and robust standard errors were used. Detailed regression results, including those with other dependent variables, can be found in Appendix Table 9.

In Table 5, it can be observed that CEO changes are associated with an average decrease in returns of 0.046% per month over a period of 16 months. Conversely, when looking forward, an average increase in returns of 1.3% per month is found following a CEO change. Yet, when considering the surprise-based matched control group, these coefficients change. The one-month return now decreases by an average of 0.2% post-dismissal, while the counterfactual shows an average increase of 0.2% per month. This suggests that the damage caused by CEO changes is more significant than the reversal to the mean effect. In the long term, the 0.59% extra return is still lower than the 0.89% achieved without a dismissal, but it becomes positive. These findings imply that CEO changes have a negative impact on stock prices, and that the effects persist longer than expected, masked by the reversal to the mean.

Interestingly, the second counterfactual group, based on excess returns and analyst expectation distances, shows much smaller effects for the counterfactuals. Although statistically significant, these effects are significantly lower than those observed for the actual change variables. The F-test rejects equivalence of the two parameters suggesting that there is a different effect under the counterfactual. Based on the analysis, it can be argued that CEO change has a statistically significant effect on the firm's performance, as indicated by the stock market proxy, however, it might also just be a reversal to the mean influenced downwards by the announcement of a CEO change as shown to exist by Dedman and Lin (2002). The main difference between the distance and surprise based matching can be attributed to the likely poor matching based on excess returns in the distance based matching.

Table 5: Regression Results: Effect of CEO Changes on Return and Cumulative Excess Return

(x100)	Return	Cumulative Excess Return (+3)
Actual Change	-0.046 (-3.41)***	1.309 (15.04)***
Surprise based matching		
Change	-0.228 (-17.81)***	0.591 (7.79)***
Change Counter	0.279 (10.54)***	0.885 (6.8)***
F-test	0.00	0.03
Distance based matching		
Change	-0.265 (-20.04)***	0.571 (7.23)***
Change Counter	-0.01 (-0.55)	0.340 (3.83)***
F-test	0.00	0.02

Notes: Actual Change is the dummy coefficient in the naive regression. For both counterfactual selection methods the dummies are displayed; Change is the actual change again and Change Counter is the counterfactual dummy variable. Additionally, the F-test for equivalence of the parameters is shown. Surprise-based matching matches on the cumulative surprise in the prior month and Distance-based matching matches on the Euclidean distance between cumulative surprise and excess returns in the prior month.
*** (**) indicates significance at 1% (5%)

The dismissal regressions exhibit similar patterns, as shown in Table 6. The actual dismissal dummy variable is smaller and not statistically significant at -0.032 for the return. However, the 3-month variable is highly significant, indicating an increase of 0.89% in returns per month. This contrasts with the increase observed for the change dummy, suggesting that firing a CEO is less effective than having the CEO voluntarily quit, which is logical as it does not imply an underlying problem in the company's strategy or ethics. In the analysis of matched testing, the dismissal and control dummies show similar patterns to the change dummy. The only significant difference is observed in the dismissal control dummy for the 3-month excess return, which exhibits an average increase of 0.486% after a dismissal, compared to 0.545% for the dismissal dummy.

Regarding the distance-based matching, a similar pattern is observed as in the overall changes, with the dismissal counter dummy now also being statistically significant at 0.128% of extra return on average per month. This suggests that the distance-based matching method may have performed better in capturing the actual dismissals, as there was more significant stock movement prior to the dismissal to react to. It is worth noting that this poor stock performance associated with dismissals has already been documented in the literature by Ertugrul and Krishnan (2011), and was also found in the earlier logit tests.

Another notable pattern is the positive coefficient for the control group, while the actual group remains negative in the one-month return in the matched data. This suggests that the overall negative stock movements observed are related to the dismissal itself. This highlights a limitation of using stock prices as performance measures for firms, as they are influenced by announcements and public opinion, meaning that they can increase or decrease even without any change in firm performance. Therefore, the one-month return metric might not be the most suitable metric for evaluating the performance of firms undergoing CEO changes. On the other hand, the 3-month excess return aligns more closely with the counterfactual and can be described as a reversion to the mean effect, as supported by the F-test that does not reject the equivalence of the two parameters in both matched regressions.

Table 6: Regression Results: Effect of Dismissals on Return and Cumulative Excess Return

(x100)	**Return**	**Cumulative Excess Return (+3)**
Actual Dismissal	-0.032 (-1.25)	0.891 (4.95)***
Surprise based matching		
Dismissal	-0.204 (-7.89)***	0.545 (3.06)***
Dismissal Counter	0.304 (5.14)***	0.486 (2.05)**
F-test	0.00	0.84
Distance based matching		
Dismissal	-0.205 (-7.92)***	0.550 (3.09)***
Dismissal Counter	0.128 (3.34)***	0.365 (2.11)**
F-test	0.00	0.44

Notes: Actual dismissal is the dummy coefficient in the naive regression. For both counterfactual selection methods the dummies are displayed; dismissal is the actual dismissal again and dismissal Counter is the counterfactual dummy variable. Additionally, the F-test for equivalence of the parameters is shown. Surprise-based matching matches on the cumulative surprise in the prior month and Distance-based matching matches on the Euclidean distance between cumulative surprise and excess returns in the prior month.
*** (**) indicates significance at 1% (5%)

In summary, the findings indicate that there is no significant effect on team performance following a coach dismissal, and similarly, there is no significant positive effect on company performance following a CEO dismissal. Although the coach change in football does not appear to have an impact on performance overall, I have observed that the coefficients for CEOs are significantly different, albeit in the same direction. This suggests that the regression to the mean may still be plausible, but the adjustment process may be slower for newly appointed CEOs.

6 Conclusion

In conclusion, this study aimed to extend current academic work on CEO dismissals by leveraging methods and insights derived from sports-based research. The goal was to compare the results and assess the viability of using sports as a proxy to test labour economic theories.

The logit-based models employed in this study revealed that CEOs and coaches are dismissed for similar reasons, highlighting the significance of performance metrics such as excess returns and points scored, as well as third-party estimates like analyst estimates and bookmaker odds. However, the findings did not provide substantial statistically significant evidence for subsequent performance improvement following managerial changes.

Specifically, the results align with the findings of Van Ours and Van Tuijl (2016) as no significant difference between coach changes and the control group was found, suggesting that the observed performance increase is likely a regression to the mean. Even in the sensitivity analysis with less extreme parameters, I was unable to establish significant differences in the results.

Regarding the CEO data, the observed performance increases after dismissals occurred in both the actual dismissals and the control group. However, the control group exhibited higher coefficient values than the actual dismissals, implying that in the short event window of our research, CEO changes may actually have a detrimental effect on company performance, as measured by stock prices. This contradicts existing research suggesting that new CEOs tend to perform better in the long run, suggesting the event window used may have been too short.

However, overall, this study indicates that there is no significant evidence supporting improved performance following CEO and coach changes. This suggests that sports can serve as a reliable proxy for real-life businesses in the case of management dismissals and to some degree validates the use of sports-based research to test labour economic theories. This comparison has significant implications, as it opens avenues for further exploration of labour economic theories in sports. Yet, we must always be cautious and periodically check whether our sports-based experiments remain comparable.

Still, it is essential to acknowledge the limitations of this study. The CEO data exhibited signs of performance increases, but capturing them accurately was challenging due to the proxy of returns, including excess returns. The selection of the control group for CEO data was also more intricate, potentially impacting the results. Future research opportunities lie in refining CEO performance metrics, which are inherently challenging due to the lack of real-time financial data, and incorporating more up-to-date analyst estimates to enhance accuracy. Data was also relatively scarce in the coach dataset with only 59 actual coach changes, something that can be solved by finding a larger dataset for a league, considering multiple countries, or even looking at other sports such as American football or baseball.

Additionally, addressing selection bias in the CEO dataset, which only includes well-known American CEO dismissals, should be considered. Nevertheless, the large quantity of data used in the study reduces the potential impact of this bias. The coach data also faces selection bias, as football boards or owners may choose not to fire a coach when they perceive a better future ahead, resulting in counterfactual scenarios with significant performance increases. Conversely, they may opt to switch coaches when facing a perceived decline, leading to a revival, where there may not have been one if the coach had stayed. Thus, the selection of counterfactual observations may not be entirely justified due to the inherent selection bias.

Further research includes exploring better ways to proxy CEO performance metrics given the challenges of using real-time financial data and considering alternative measures to accurately capture performance. Additionally, analyst estimates may be included in real time if more frequent data points become available. Another avenue for future research is re-estimating the logit model that describes dismissal reasons to incorporate more parameters, for example, related to relegation, as found in prior literature. Similarly, other model types like mixed logit regressions or duration models can also be estimated to better compare the CEO and coach data. Furthermore, exploring different time intervals for assessing CEO dismissal results can provide valuable insights into the long or short-term effects.

To summarize the study highlights the effectiveness of sports based experiments in substantiating managerial theory. Suggesting that S&P1500 companies and Dutch football clubs have a lot more in common than they previously expected.

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7 Appendix

7.1 Additional Data Description Coach Data

Table 7: List of coach changes and dismissals in the dataset of Van Ours and Van Tuijl (2016)

Season	Game	Club	All	D	Season	WNR	Club	All	D
2003-2004	12	ADO Den Haag	1	0	2012-2013	10	NAC Breda	1	1
2006-2007	14	ADO Den Haag	1	0	2004-2005	17	NEC	1	1
2009-2010	30	ADO Den Haag	1	1	2005-2006	17	NEC	1	0
2013-2014	23	ADO Den Haag	1	1	2009-2010	12	NEC	1	0
2000-2001	27	AZ	1	0	2007-2008	10	PSV	1	0
2002-2003	10	AZ	1	1	2008-2009	20	PSV	1	1
2009-2010	17	AZ	1	1	2011-2012	26	PSV	1	1
2013-2014	9	AZ	1	1	2002-2003	18	RBC Roosendaal	1	1
2001-2002	15	Ajax	1	1	2004-2005	29	RBC Roosendaal	1	1
2004-2005	23	Ajax	1	0	2005-2006	19	RBC Roosendaal	1	1
2007-2008	8	Ajax	1	0	2006-2007	15	RKC Waalwijk	1	1
2010-2011	18	Ajax	1	0	2001-2002	5	Roda JC	1	1
2013-2014	30	Cambuur Leeuwarden	1	1	2006-2007	23	Roda JC	1	0
2000-2001	15	De Graafschap	1	1	2008-2009	6	Roda JC	1	1
2008-2009	25	De Graafschap	1	1	2013-2014	18	Roda JC	1	1
2011-2012	22	De Graafschap	1	1	2009-2010	6	SC Heerenveen	1	1
2004-2005	24	FC Den Bosch	1	1	2000-2001	22	Sparta Rotterdam	1	1
2002-2003	9	FC Groningen	1	0	2007-2008	12	Sparta Rotterdam	1	1
2005-2006	22	FC Twente	1	0	2010-2011	19	VVV-Venlo	1	1
2011-2012	18	FC Twente	1	1	2011-2012	16	VVV-Venlo	1	0
2012-2013	25	FC Twente	1	1	2001-2002	15	Vitesse	1	0
2008-2009	17	FC Utrecht	1	1	2002-2003	26	Vitesse	1	1
2011-2012	10	FC Utrecht	1	0	2008-2009	18	Vitesse	1	1
2003-2004	19	FC Volendam	1	1	2010-2011	10	Vitesse	1	1
2003-2004	6	FC Zwolle	1	1	2003-2004	17	Willem II	1	0
2008-2009	18	Feyenoord	1	1	2005-2006	13	Willem II	1	1
2000-2001	14	Fortuna Sittard	1	1	2007-2008	11	Willem II	1	1
2001-2002	17	Fortuna Sittard	1	1	2008-2009	24	Willem II	1	0
2007-2008	17	Heracles Almelo	1	1	2009-2010	24	Willem II	1	1
2005-2006	18	NAC Breda	1	1					

All refers to a coach change including quits and dismissals and D refers to a dismissal. All games are indicated by the club, the game number in the season (1-34), and the season itself.

7.2 Results Full Coach Regressions

Table 8: Full regression models for coach changes and dismissals

Regression Coach Changes and Dismissals						
	Actual Changes	*Matched Changes*	*Matched Changes Sensitivity*	*Actual Dismissals*	*Matched Dismissals*	*Matched Dismissals Sensitivity*
Points						
Position Opponent	0.062 (13.42)	0.06 (15.83)	0.061 (15.85)	0.06 (11.17)	0.06 (13.83)	0.059 (13.22)
Home Game	0.639 (12.77)	0.612 (14.9)	0.608 (14.78)	0.663 (11.26)	0.614 (13.03)	0.604 (12.63)
Change	0.253 (4.73)	0.252 (4.21)	0.252 (4.21)			
Change Counter		0.202 (2.75)	0.205 (2.83)			
Dismissal				0.293 (4.59)	0.282 (4.08)	0.283 (4.09)
Dismissal Counter					0.223 (2.62)	0.192 (2.23)
Wins						
Position Opponent	0.019 (11.11)	0.019 (13.24)	0.019 (13.47)	0.018 (9.03)	0.018 (11.23)	0.018 (10.93)
Home Game	0.215 (11.68)	0.197 (12.97)	0.194 (12.75)	0.219 (10.21)	0.199 (11.52)	0.194 (11.1)
Change	0.089 (4.52)	0.095 (4.3)	0.095 (4.3)			
Change Counter		0.067 (2.54)	0.067 (2.54)			
Dismissal				0.104 (4.49)	0.103 (4.07)	0.103 (4.08)
Dismissal Counter					0.07 (2.31)	0.054 (1.76)
Goal Difference						
Position Opponent	0.114 (15.44)	0.113 (18.96)	0.111 (18.39)	0.118 (13.6)	0.118 (17.11)	0.114 (16.04)
Home Game	1.034 (13.35)	1.06 (16.82)	1.058 (16.61)	1.095 (11.85)	1.064 (14.58)	1.053 (14.03)
Change	0.373 (4.45)	0.374 (4)	0.374 (4)			
Change Counter		0.273 (2.37)	0.199 (1.7)			
Dismissal				0.484 (4.85)	0.458 (4.21)	0.46 (4.23)
Dismissal Counter					0.312 (2.33)	0.149 (1.04)
N	2006.000	(3128.00)	3094.000	(1428.00)	2346.000	(2278.00)
n	59	92	91	42	69	67

All coefficients are followed by their own t-statistic between brackets. Position of Opponent is equal to the rank of the opposing team in the prior year, and Home Game is a dummy set to 1 if the game was played at home. The remainder are the dummy variables for dismissal/change set to 1 if it occurred, for example, Change Counter is the dummy variable for the counterfactual of a coach change.

7.3 Results Full CEO Regressions

Table 9: Full model results for all CEO change regressions

	Return	Return (+1)	Cumulative Return (-3)	Cumulative Return (+3)	Cumulative Excess Return (-3)	Cumulative Excess Return (+3)
All CEO changes & cumulative surprise						
Intercept	0.007 (73.44)	0.005 (35.69)	0.025 (48.39)	0.011 (22.9)	-0.002 (-3.58)	-0.004 (-8.63)
Cumulative S&P Return (-3)	0.001 (1.15)	0.388 (221.75)	-0.023 (-3.86)	1.146 (171.2)	-0.086 (-16.45)	0.003 (0.43)
S&P Return	1.126 (445.95)	0.271 (96.81)	0.762 (79.96)	-0.075 (-7.78)	-0.043 (-5.32)	-0.077 (-8.82)
S&P Return (-1)	0.005 (3.14)	-0.137 (-52.07)	0.841 (80.7)	-0.019 (-2.11)	-0.006 (-0.69)	-0.023 (-2.81)
Excess Return (-1)	1.014 (444.3)	0.004 (3.73)	0.986 (65.65)	0.015 (1.3)	0.961 (76.37)	0.006 (0.54)
Excess Return	0.006 (2.17)	1.01 (548.64)	0.004 (0.39)	1.000 (48)	0.006 (0.67)	0.953 (42.11)
Change	-0.002 (-17.81)	-0.002 (-10.86)	-0.003 (-3.87)	0.002 (2.15)	0.001 (1.81)	0.006 (7.79)
Change Counter (Surprise)	0.003 (10.54)	0.002 (6.28)	0.007 (4.72)	0.013 (8.92)	0.006 (4.14)	0.009 (6.8)
All CEO changes & distance based selection						
Intercept	0.007 (73.81)	0.006 (35.41)	0.025 (44.81)	0.012 (23.12)	-0.002 (-3.87)	-0.004 (-7.45)
Cumulative S&P Return (-3)	0.001 (1.13)	0.388 (221.61)	-0.023 (-3.9)	1.145 (170.88)	-0.087 (-16.53)	0.002 (0.35)
S&P Return	1.126 (445.68)	0.271 (96.81)	0.762 (79.92)	-0.075 (-7.76)	-0.044 (-5.37)	-0.077 (-8.85)
S&P Return (-1)	0.005 (3.2)	-0.137 (-52.01)	0.841 (80.65)	-0.019 (-2.09)	-0.007 (-0.76)	-0.024 (-2.85)
Excess Return (-1)	1.015 (444.58)	0.005 (3.75)	0.986 (65.66)	0.015 (1.32)	0.961 (76.38)	0.006 (0.54)
Excess Return	0.006 (2.19)	1.01 (548.75)	0.004 (0.41)	1 (47.98)	0.006 (0.68)	0.953 (42.11)
Change	-0.003 (-20.04)	-0.003 (-11.69)	-0.004 (-4.23)	0.001 (0.61)	0.002 (2.15)	0.006 (7.23)
Change Counter (Combination)	0 (-0.55)	0 (0.64)	0.002 (1.6)	0.001 (1.17)	0.004 (4.42)	0.003 (3.83)
CEO dismissals & cumulative surprise						
Intercept	0.007 (83.09)	0.005 (39.23)	0.025 (58.53)	0.012 (30.91)	0 (-1.1)	-0.002 (-5.25)
Cumulative S&P Return (-3)	0.002 (1.55)	0.388 (222.13)	-0.022 (-3.78)	1.146 (171.18)	-0.087 (-16.54)	0.002 (0.26)
S&P Return	1.126 (446.37)	0.271 (97.16)	0.763 (80.06)	-0.075 (-7.75)	-0.044 (-5.35)	-0.078 (-8.89)
S&P Return (-1)	0.006 (3.53)	-0.136 (-51.91)	0.842 (80.86)	-0.019 (-2.08)	-0.006 (-0.73)	-0.024 (-2.91)
Excess Return (-1)	1.015 (444.41)	0.004 (3.73)	0.986 (65.66)	0.015 (1.32)	0.961 (76.39)	0.007 (0.55)
Excess Return	0.006 (2.18)	1.01 (548.59)	0.004 (0.41)	1 (47.99)	0.006 (0.69)	0.953 (42.11)
Dismissal	-0.002 (-7.89)	-0.002 (-5.17)	-0.009 (-4.15)	0.002 (1.27)	-0.006 (-3.23)	0.005 (3.06)
Dismissal Counter (Surprise)	0.003 (5.14)	0.002 (2.31)	0.003 (0.99)	0.009 (3.48)	-0.001 (-0.21)	0.005 (2.05)
CEO dismissals & distance based selection						
Intercept	0.007 (82.83)	0.005 (38.87)	0.025 (58.1)	0.012 (30.64)	-0.001 (-1.3)	-0.002 (-5.33)
Cumulative S&P Return (-3)	0.002 (1.55)	0.388 (222.14)	-0.022 (-3.78)	1.145 (171.14)	-0.087 (-16.55)	0.002 (0.26)
S&P Return	1.126 (446.35)	0.271 (97.15)	0.763 (80.05)	-0.075 (-7.76)	-0.044 (-5.36)	-0.078 (-8.9)
S&P Return (-1)	0.006 (3.52)	-0.136 (-51.91)	0.841 (80.84)	-0.019 (-2.09)	-0.007 (-0.74)	-0.024 (-2.92)
Excess Return (-1)	1.014 (444.38)	0.004 (3.73)	0.986 (65.66)	0.015 (1.32)	0.961 (76.39)	0.007 (0.55)
Excess Return	0.006 (2.17)	1.01 (548.61)	0.004 (0.41)	1 (47.99)	0.006 (0.69)	0.953 (42.11)
Dismissal	-0.002 (-7.92)	-0.002 (-5.12)	-0.009 (-4.15)	0.002 (1.27)	-0.006 (-3.18)	0.006 (3.09)
Dismissal Counter (Combination)	0.001 (3.34)	0.001 (2.66)	0.002 (0.85)	0.005 (2.44)	0.002 (1.02)	0.004 (2.11)

All dependent variables are regressed on the last month value-weighted index return, the coming three months of index return, the last three months of index return, excess return over the last month and excess return over the prior month. T-statistics are in brackets.