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Special ones? The effect of head coaches on football team performance

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Abstract

Using data from professional football leagues in four countries, we assess the effects on team performances following head coach turnover, distinguishing between voluntary and involuntary exits. We use entropy balancing to deal with the endogeneity of coach departures, by reweighting pre-departure covariates to obtain a comparable control group. Results reveal little, if any, positive effect from either type of turnover, though some longer-term benefits are possible if teams experience no subsequent turnover. We discuss how these findings fit with previous literature and theory, and discuss the wider practical implications.

KEYWORDS

entropy balancing, football, managerial performance, team performance

JEL CLASSIFICATION

J63, Z21, Z22

1 | INTRODUCTION

Across a range of disciplines there is a strong prior that leaders affect performance. In military history, leaders on the battlefield are credited for victories and blamed for defeats linked to their strategies, while the tactics of leaders of political parties may be called into question following a poor-election result. Economists have long maintained that the person who leads an organisation can have a substantial effect on its productivity. This is because the quality of leaders' decision-making and leaders' own productivity can have profound implications for the way the organization is run and thus the productivity of those further down the corporate hierarchy (Rosen, 1990).

Lazear et al. (2015) confirm this to be true; an average boss adds roughly 1.75 times more to output than an average worker, with peer effects paling into economic insignificance relative to the effects of bosses.

It has, however, been very difficult to identify a causal impact of managers on performance outcomes because managers are not randomly assigned to organizations and changes in corporate leadership are usually endogenous. For this reason, some analysts have relied on unforeseen death or hospitalisation episodes to identify the effects of leaders on performance. Bennedsen et al. (2020) use hospitalization episodes to identify the effects of CEOs on corporate performance while Besley et al. (2011) use the sudden death of heads of state to establish the importance of leaders' education for growth in countries' gross domestic product.

In this article, we focus on the role of the head coach in determining sports teams' performances. The role of the head coach can vary across sports and even within a sport across countries. But in our setting of professional football (soccer), they typically appoint their backroom and support staff, pick the team for each game, develop player skills, decide on match tactics, and in some cases have input into player recruitment decisions. It seems reasonable to conjecture, therefore, that head coaches play a crucial role in determining team performance. Yet the literature finds little evidence of a positive performance effect following a change in head coach. This seems somewhat surprising since hiring is costly to firms and club owners should, in principle, have the information required to ensure a good person-job match since weekly football matches provide regular updates on the quality of potential candidates.

Using a large, rich data set on head coaches from the top two tiers of four European countries (France, Germany, Italy and Spain) over the seasons 2000/01 to 2014/15, we use entropy balancing to estimate the effects of a change in head coach on team performance measured as points achieved in league games played. We contribute to existing literature by distinguishing between circumstances in which the coach is dismissed (a forced exit), and circumstances in which the coach quits (a voluntary exit). In line with most of the literature however, we fail to uncover a sustained positive effect of head coach turnover (of either type), though sensitivity analysis reveals some sustained positive effects may emerge following a dismissal confined to circumstances when there is no head coach turnover in a subsequent 20 game period. We offer some thoughts on why this may be the case. There is less evidence of a change in performance after a head coach quits, though some longer-term effects are apparent. Previous studies have not been able to make this distinction between dismissals and quits or, if they have, their sample sizes have been insufficient to provide the necessary statistical power to identify coach effects.

In Section 2, we review the literature on head coaches and football team performance, identifying the ways in which our paper builds on the existing literature. In Section 3, we present our data and estimation techniques. Section 4 presents the results before concluding in Section 5.

2 | THEORY AND EMPIRICAL EVIDENCE

2.1 | Theoretical background

According to job match theory, workers are hired when the match-specific surplus generated for the firm exceeds the costs of hire. Termination of the contract will occur either through dismissal by the employer (a forced turnover) or a quit by the worker (a voluntary turnover), where the value of that match for one or both parties falls below the value of an outside option (Farber, 1999). In football, club owners can update their information on head coach performance with the results from each game, which tend to happen on average once a week during the football season. This provides them with an opportunity to consider head coach performance relative to expectations on an almost continual basis. Evaluating performance is harder to do in other settings where principals may only receive reports of executive performance in the annual financial accounts, while monitoring executive performance may prove costly. Football club owners act on this information: Bryson et al. (2020) find that dismissals accounted for over 70% of all head coach departures and that the gap between actual team performance and expected performance (captured by betting odds) is a strong predictor of dismissals.

For the football team, the outside option is an alternative head coach. If head coaches are heterogeneous in ability, then teams should be able to replace a departing coach with a better one. Muehlheusser et al. (2016) confirm that there is substantial heterogeneity in head coach ability in the German Bundesliga, and that team performance varies according to the ability of the incoming coach. As to why a new coach might improve team performance, it could simply be that they bring in fresh ideas (Muehlheusser et al., 2016) in the form of new tactics. Moreover, players may 'step-up' their efforts in an attempt to secure a place in the team under new management. We offer some more detail on potential mechanisms in Section 2.3, and offer some insights as to why the short- and long-run effects of a coach may differ.

However, there are also a number of reasons why owners may be unable to improve team performance through the recruitment of a new coach. First, while head coaches are heterogeneous in ability, it will be difficult for club owners to identify which are the more talented among them. Their past performance may be attributable to factors other than ability, including luck, so it is not possible to read off coach talent directly from their past performance. Second, teams may be constrained in the talent they can attract. Theory suggests inefficient hiring in talent markets whereby mediocre workers are re-hired in the face of the risk associated with appraising the talent of workers that are new to an industry (Terviö, 2009) as there is a substantial amount of uncertainty about the talent of entry-level workers. Peeters et al. (2022) confirm that this market failure exists among head coaches in professional football in England. In particular, they report that about one-quarter of rehired coaches are of lower ability than an average entrant, with clubs in lower divisions making more substandard hires. As such, the scope for poaching coaches appears to be limited to a select number of cases, with only limited numbers of "good coaches" available to be poached. This inefficiency is not limited only to the football industry however, (see for example Pallais (2014) for the case of the online hiring of inexperienced data entry specialists). More broadly, it would be characterised by cases where talent is industry-specific, is only revealed on the job and, once revealed, becomes public information. Terviö (2009) points to entertainment industries and top management positions as industries that meet these criteria. As a result, more productive firms hire those revealed to be high ability, whereas less productive firms must experiment with untested new workers. Where there is insufficient discovery of new talent firms tend to re-hire some workers known to be mediocre. Of course, while this may be inefficient, the upshot for inexperienced coaches is that lower ranked teams have clear incentives to hire novices. Finally, it is uncertain a priori just how much of the "talent" head coaches possess is generalizable and how much is team-specific. If there is a large job-match specific component, performing well in one setting may not translate to good performance in a new setting.

For the head coach, the outside option comes in the form of alternative employment. Clubs searching for a new head coach have three possible options: recruit from the pool of unattached coaches, promote from within, or poach another club's head coach. The latter involves a head coach quitting their current post to take up their new job, and the recruiting club is likely to have to pay a release clause to begin talks. One would assume that better or over performing head coaches are the primary targets for recruiting clubs. However, the effect on the performance of the club losing their head coach is unclear since a club would not necessarily have planned for this event (unlike a dismissal) and seemingly had no intentions to part ways with the current coach if the job match were already optimal. It is therefore unclear, a priori, what impact a head coach quit will have on team performance.[1]

[1]In reality, quits could involve multiple subcategories. A quit could be, as we describe, a coach getting a better offer from another team. On contrary, a coach may decide to quit for other reasons, for example, fearing a downturn in form. Indeed, we see about a 50–50 split of coaches quitting for a team higher up or lower down the league rankings (notwithstanding the obvious problem of interpreting league position as a measure of team quality/prestige). Theoretically, however, this distinction is less important. A quit, as laid out by Farber (1999) is a decision made by the agent, so they are assumed to be decisions that maximize their utility, however that is perceived.

2.2 | Empirical evidence

Since Head Coaches in professional football typically appoint backroom support staff, pick the team for each game, decide on match tactics and, in some cases, have the input into recruitment of football players to the squad, it would not be surprising to find that teams who dismiss poorly performing coaches see performance improve with a new in-coming coach. Yet this is not what is found in most of the literature. In their review of the recent literature on head coaches and football team performance, Van Ours and Van Tuijl (2016) identify eleven studies published since 2000 analysing the period 1993–2010 spanning six countries. None of them identify a positive effect of an incoming coach following a coach dismissal.[2]

However, there are some important limitations to the studies reviewed. First, with the exception of Dobson and Goddard (2011), they rely on a small number of coach dismissal observations, and typically in a single league. Second, they tend to report changes over relatively short periods of time (usually four games) which may be insufficient to pick up performance changes if head coaches take some time to "make their mark". This would appear likely given the need to adjust to a new environment, alter the composition of the squad, implement tactics, and hire their own backroom staff. Third, many studies rely on difference-in-difference estimates that do not provide a convincing counterfactual to the dismissal spells.

Van Ours and Van Tuijl (2016) address some of these issues. They deploy a nearest neighbour matching strategy using the gap between team performance and expected performance (measured using betting odds) to match team spells with dismissals against team spells from the same team that experienced similar patterns in performance and expected performance but did not switch head coach. This strategy offers a much more plausible counterfactual against which to judge the performance effects of an in-coming head coach. They find performance improves after coach dismissal, but the same improvement is observed in counterfactual cases, leading the authors to conclude that they are simply observing "a regression to the mean phenomenon" (p. 602). However, their study also suffers from small sample sizes, something that particularly affects their ability to estimate models for the subset of cases where head coaches quit. They also combine estimates for short and long follow-up spells without identifying the short and long-run effects of a coach switch.

Using game-level data from 19 seasons of Danish top-division football, Madum (2016) also investigates team performance after head coach departures using a nearest neighbour matching estimator, matching on the recent team and opposition performance and league ranking, but not expected performance derived from betting odds. Madum's findings contrast with most of the literature, uncovering some positive effects of an incoming coach relative to counterfactual scenarios, but the performance only improves in home games. Tena and Forrest (2007) find similar results for Spain although they did not use matching methods.[3] Madum also shows that the effect is apparent only for those teams that fired coaches (the average treatment-on-the-treated effect) but that the effect would have been absent among the non-treated, a finding that suggests team owners behave optimally when deciding whether to dismiss poorly performing coaches. More recently, Galdino et al. (2021) report largely insignificant effects of coach turnover in the Brazilian top division, though their estimates rely on OLS models with no attempt to form a counterfactual group.

Outside of professional football, Goff et al. (2019) report estimates for the effect of both head coach changes and General Manager (GM) changes across the National Football League (NFL), Major League Baseball (MLB) and the National Basketball Association (NBA). They find some positive effects for changing a head coach, most notably in the NFL where a new coach contributes between 0.5 and 1.2 extra wins per season (in a 16-game season). However, their estimates fail to deal with the endogeneity of both coach and GM departures. Effects of changing coaches in the other two leagues were less pronounced, while a new GM was found to have virtually zero impact on team performance. Aside from team performance, Bradbury (2017), for the case of MLB, and Berri et al. (2009) for the case of the NBA

[2]Though, as Goff et al. (2019) rightly point out, this is not to say that the role of a head coach is unimportant, more that the person who fills the role does not matter. They say that because the ability distribution of the candidates is so compressed, it is unlikely that a new candidate can make a difference.

[3]In contrast, Muehlheusser et al. (2016) find performance improvements among German teams are driven by away matches.

also find that coaches have little impact on individual player performances, at least on average. Both articles use size and significance of coach fixed effects for their evaluations. Bradbury (2017) further reports that hiring a new coach is associated with gains in attendance of up to 1000 spectators per game, compared to an average of a little under 31,000.

2.3 | Contributions

Our estimates differ somewhat from those in the literature in several respects. Most importantly, because our data are large enough, we can be confident in identifying even quite small effects, not only for dismissals but also for quits on changes in team performance. To the best of our knowledge, we are the first article that can make this distinction between these two theoretically different events.[4] Quits are decisions made by agents, rather than principals, so they may be less likely to lead to improvements in team performance, at least in the longer term, since the principal was otherwise happy to keep the incumbent coach. Second, we estimate performance outcomes over a longer period (20 games, roughly half a season) of time to establish whether any effects of a coach change differ in the short and longer terms. Below, we argue how and why these effects may differ. We also use entropy balancing to construct counterfactual spells to those ending in quits or dismissals.

We test the hypothesis that fires result in performance improvements, notwithstanding the caveats outlined above, but quits are less likely to do so. Because we track head coaches over longer periods of time, we compare and contrast short- and longer-run performance effects, by estimating separate models for points per game achieved over the subsequent 1 to 20 games, as well as effects across seasons. This distinction is important in picking up quite separate effects of head coach changes on team performance. The short-run effect is the "bump" in performance that is attributable to simply making a change. There are two aspects to this. The first is the one football pundits often refer to, namely, the motivational impact of a new coach on current players who seek to impress the new coach to cement their place in the team. The second element that might have an immediate impact on performance is simply the fact of having made a change. Levitt (2021) finds there are happiness benefits of making life-changing decisions when determined by the toss of a coin - that is, even when the decision is made based on a random event. Analogously, it seems reasonable to assume that a simple change in coach, regardless of the incoming coach's quality or the circumstances surrounding his appointment (i.e. following a quit or dismissal of the previous coach), may result in improvements in team performance.

The longer-run impact of a change in head coach will arise where coaches benefit from on-the-job learning, which is likely to be a two-way process between coach and players. The coach will learn about the new football club, its players and the expectations and orientation of the owners. Coaches will also be able to sell unwanted players and recruit new ones via the transfer market, though this will take time as transfers only occur during limited windows during the year. Recent studies emphasise the importance of on-the-job learning for individual worker productivity (e.g. Gaynor et al. (2005) in the health economics literature), especially among new hires (De Grip, 2015).[5] The players may also take time to adapt and learn about the new coach's training and fitness regimes, including learning new formations, play styles, etc. We look directly at time-variance in any performance effects. More nuanced tactical changes (formation changes, play–style changes, etc.) are possible, but harder to measure with any accuracy, and might plausibly occur both in the short and longer run.

[4]That is, for the football industry. Gregory-Smith et al. (2009) analyse the factors associated with CEO dismissals and retirements, though they do not estimate the resulting effects on firm performance.

[5]Perhaps the most successful football club manager of all time, Sir Alex Ferguson, described the time it took to "build a club" (https://hbr.org/2013/10/fergusons-formula). Yet, he was not successful in his early years as he recalled in his autobiography: "After the farewell in May 2013, the pivotal moments filled my thoughts. Winning that FA Cup third-round tie against Nottingham Forest in January 1990, in which a Mark Robins goal sent us on our way to the final when my job was supposedly on the line. Without the FA Cup [final] victory over Crystal Palace nearly four years after my arrival, grave doubts would have been raised about my suitability for the job. We will never know how close I was to being sacked because the decision was never forced on the United board. But without that triumph at Wembley, the crowds would have shrivelled. Disaffection might have swept the club" (Ferguson, 2013).

TABLE 1 Frequency of exits (by type) per season.

Season	Dismissals	Quits
2000–01	70	20
2001–02	61	34
2002–03	63	26
2003–04	71	43
2004–05	63	36
2005–06	74	31
2006–07	79	39
2007–08	69	34
2008–09	95	44
2009–10	112	29
2010–11	99	38
2011–12	111	39
2012–13	99	36
2013–14	110	28
2014–15	151	56
Total	1327	533

3 | DATA AND EMPIRICAL APPROACH

Our data consist of all games from the top two divisions of four major European football leagues (France, Germany, Italy and Spain) over the period 2000/01 to 2014/15 for which we can precisely ascertain the start and end dates of managerial spells.[6] This period covers 273 teams, with 769 individual coaches taking charge of games for those teams. Coaching tenures were hand-collected from *Wikipedia*, supported by online newspaper sources from each country. In line with literature such as Van Ours and Van Tuijl (2016), we exclude caretaker spells where an interim coach took over management of a team prior to a permanent appointment. It could be that an interim candidate performs well enough to be given the job on a full-time basis; in this case we only consider the date from when they were permanently appointed. In aggregate, we have 1327 fires and 533 quits, which on average lasted for 35 (standard deviation = 31) and 60 (standard deviation = 51) games, respectively. Our recording of quits and dismissals is taken from Wikipedia entries on head coach biographies and summaries of league seasons, cross checked with local media sources. In cases where the cause of departure was listed as 'mutual consent', these are classed as dismissals. In reality, these are circumstances where a coach has been asked to leave, but is officially announced as a joint decision, allowing the coach to 'save face'. Table 1 shows the number of dismissals and quits per season, aggregated over the leagues in our data. Dismissals exceed quits and there appears to be a rising trend in both dismissals and quits. The increased firing rate may be a consequence of growing revenue differences between league positions and tiers in European football.[7] This increase in reward for success was proposed by D'Addona and Kind (2014) as an explanation for increased head coach turnover in English football in their study covering the post-war period up to 2008.

[6]We exclude the English leagues from our analysis since many teams in England operate with a manager rather than a head coach. Typically, a manager will be involved in the same roles as a head coach (coaching the team, picking the matchday squads, motivating players, etc.) with added responsibilities such as recruitment and overseeing the progression of youth players into the senior team. In European football, teams now typically operate with a head coach and a director of football who takes on the other responsibilities, typically with input from the head coach.

[7]Prominent amongst the sources of revenue differences between league positions is the growth of UEFA Champions' League revenues for the top three or four teams that qualify for this competition from our four sample Leagues. These revenues have grown substantially over time prompting increased investment in playing squads by aspiring teams (Green et al., 2015). Though, judging coaching performance by European success will only apply to a very small number of (elite) clubs in our data.

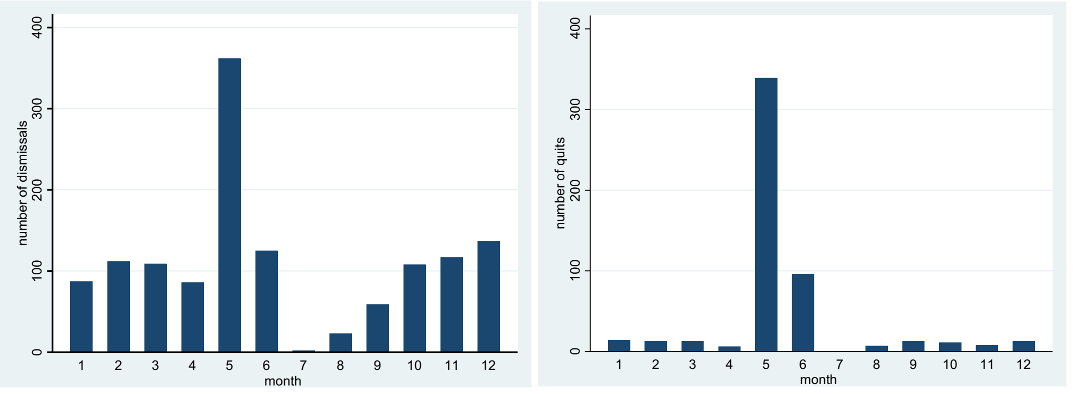

FIGURE 1 Frequency of coach exits by month (1 = January, 12 = December). The figure displays the frequency of head coach dismissals (LHS) and quits (RHS), by month across the eight leagues in our sample, from 2000/01 to 2014/15. *Source*: Author's own calculations.

Figure 1 shows the timing of dismissals and quits, respectively, as the season progresses. Time lapsed is measured monthly (as opposed to say, number of games) since the different countries and different tiers within a country have different season lengths.[8] There are large spikes in coach departures at the end of the season (usually May, though a season occasionally extends into June). This makes sense on several counts. The off season is a period with no games other than pre-season friendlies and coincides with the summer transfer window. Together, these give a new appointment the best opportunity to work with their new squad and implement any changes they deem necessary. This could entail working with the current squad of players, honing their skills, developing a playing style, and making use of the transfer market to recruit new players to the team. Moreover, the off-season is when many head coach contracts expire or are reviewed by the board of directors, so teams wishing to dismiss their coach may find it best to wait until contract expiry, rather than sacking mid-season which may require a substantial severance payment to the coach.

During the season dismissals tend to peak in mid-season when some leagues have a winter break. It appears that many clubs reassess their prospects during the winter break and are more likely to fire their head coaches at this juncture than at other points in the season. Quits on the other hand show little pattern over time. Importantly for our analysis, the two histograms give a preliminary suggestion that the statistical processes driving head coach fires and quits could well be different.

Figure 2 shows average team performance before and after coach changes, with dismissals and quits considered separately, along with spells with no coaching change (control spells). We assess team performance across the whole sample, up to 20 games before a coaching change and up to 20 games after the change, with team performance being measured as Mean Points Per Game. The blue dash-dotted line refers to performance over a control spell, the solid red line during a quit spell, and the dashed green line refers to performance during a dismissal spell.

Prior to dismissals, team performance drops as indicated by the decline in the points per game as game number zero approaches. This is akin to the Ashenfelter Dip, something one needs to be mindful of when making over-time comparisons before-and-after head coach dismissals (Bruinshoofd & Ter Weel, 2003).[9] The slight disparity between our setting of football teams and Ashenfelter's work on participants in job training programmes is that every team in our sample experiences a treatment at some point in time. Post-dismissal team performance

[8]The number of teams per leagues per season varies between 18 and 24, meaning season length varies between 34 and 46 games. Due to restructuring of leagues, bankruptcy and/or disqualification of clubs, season length may vary from year to year.
[9]The Ashenfelter Dip, first observed by Orley Ashenfelter (1978), describes the drop in the earnings of participants in job training programs in the year before entry. Thus, a simple before and after comparison of the effect of job training programs on earnings is likely to overestimate the true effect.

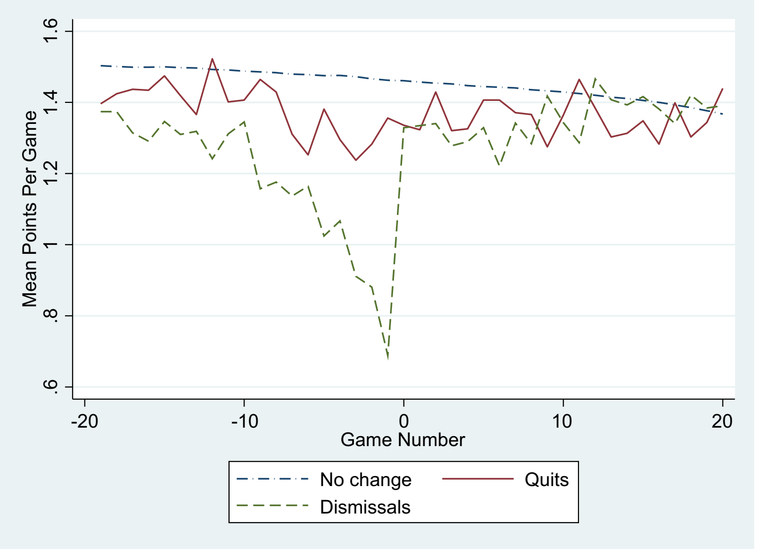

FIGURE 2 Points per game for dismissals, quits, and control spells. The figure displays the mean points per game over a 40 game spell, including 20 games pre- and post- a dismissal or quit. All the leagues and seasons included. *Source*: Author's own calculations.

recovers and stabilises at a level close to that for the pre-period. It is important to stress here, in line with De Paola and Scoppa (2012) and Van Ours and Van Tuijl (2016), this apparent jump in performance after a dismissal should not be thought of as a big jump, and instead should be considered a regression to the mean, with performance merely returning to the level it was before the drop in performance. In contrast, there is less evidence of a dip in performance prior to quits, nor much of a change in performance after a quit. The key question that we address below in more formal regression analysis is whether we can discern any causal impact of head coach turnover on team performance after accounting for the endogeneity of head coach changes and other confounding factors.

Our empirical approach begins by specifying a naïve OLS regression as follows:

$$Y_{ijk} = X'_{ijk}\alpha + \beta d_{ijk} + \epsilon_{ijk} \quad (1)$$

where the subscripts are denoted as *i* for team, *j* for game and *k* for season. This is our outcome model, where the dependent variable, Y_{ijk}, is points per game: teams get three points for a win, one for a draw and none for a defeat. We run separate models for points obtained for spells of the next single game through to longer outcome spells of up to 20 games.[10] In other words, each follow-up period is estimated from a separate regression. Match results and betting odds (which we make use of later) were provided by www.football-data.co.uk. d_{ijk} is our main variable of interest; a dummy variable to indicate whether there has been a coach change. Because we have two possible types of exit (quit or dismissal), we run the above specification twice to account for this, removing coaching tenures that end in the other type of exit (i.e. we drop spells that end in a quit when analysing dismissals and vice versa). Naturally, our test that a coach change has a positive effect on

[10]We tested the robustness of specifying the model as an OLS regression. For particularly short follow-up spells, our outcome variable points per game will appear 'lumpy', but as we extend our follow-up period, points per game will more closely resemble a continuous variable. For example, for one game, points per game can be 3, 1 or 0. For two games, points per game could be 3, 2, 1.5, 1, 0.5 or 0. As we divide a larger number of games, these 'gaps' in the outcome variable will be filled in. To address this, we used a Poisson regression which will improve the modelling in shorter spells where the outcome is essentially a count. We also tested a Generalised Linear Model, where the outcome is points share that is Points achieved divided by Maximum Attainable Points over said period. Results were identical to specifying as an OLS in both cases, and the results for these alternative models can be found in the Appendix, Tables A8 and A9.

performance is then a t-test of the null of $\beta = 0$ in Equation (1). X_{ijk} is a vector of control variables which includes information on previous team performance, captured by points per game over the previous 10 fixtures, and performance relative to expected performance (called surprise, described below). We also include opposition form, measured by the opponent's league position, and home advantage, measured by the proportion of home games over the follow up period. To complete (1), ϵ_{ijk} is a random error term. Throughout our estimations, standard errors are clustered at the team level.

Following Van Ours and Van Tuijl (2016) we incorporate a measure of Surprise which is the difference between actual and expected performance. Performance above or below expectations in any given match, or indeed across multiple games are likely to affect future performance.[11] Expected points in a given match is computed as:

$$E(Points) = (3 * Prob.\ of\ Win) + Prob.\ of\ Draw, \tag{2}$$

where the probabilities are derived from bookmakers' betting odds, accounting for the bookmaker overround.[12] Surprise is then actual points minus expected points. Naturally, a Surprise value of 0 indicates that a team performed as expected, with this being reflected by the betting market. We include Surprise in the most recent game, cumulative (total) surprise over games lagged two to five and cumulative (total) surprise over games lagged six to ten to capture any longer runs of good or bad form.

The difficulty in relying on OLS estimation of head coach changes on team performance is that head coach changes are not random. Indeed, they are likely to be endogenous with respect to team performance. To put this another way, it is likely that only the poor or underperforming teams sack their coach, as is apparent in Figure 2. Consequently, we cannot infer what would have happened to a team's performance in the absence of a head coach change by comparing the performance of teams that did and did not make a change. De Paola and Scoppa (2012), Van Ours and Van Tuijl (2016) and Besters et al. (2016) found positive and significant effects of head coach dismissals on team performance for Italian, Dutch and English football, respectively, from naïve OLS estimates only for these effects to become statistically insignificant when they compared performance with a matched comparator group.

Recognising these difficulties, we adopt a different approach to obtain the causal impact of head coach changes on team performance, namely Entropy Balancing (Hainmueller, 2012), implemented by the Stata command *ebalance* (Hainmueller & Xu, 2013). This is a data pre-processing method that reweights observations in the control group, such that the mean, variance, and skewness of the variables are equal to those in the treatment group. The control group consists of those observations where teams do not experience any coaching turnover over any 20 game period. The weights are chosen such that a loss function, describing the dissimilarity between the control and treatment variable distributions in the pre-treatment period, is minimised. The approach ultimately resembles a differences-in-differences setup, in the sense that we compare team performance following a coach turnover, to (re-weighted) control spells where teams did not experience coach turnover, assuring that treated and control groups are identical, with respect to the choice of observed covariates. Put another way, the weighting strategy tackles the issue of non-parallel trends in the pre-treated period. As such, we can think about head coach departures mimicking a random process and any selection into treatment is stripped out of the outcome Equation (1). Appendix Tables A1 and A2 show the covariate moments under both turnover events, before and after the entropy balance weights are implemented. In particular, notice how the mean, variance and

[11]As well as predicting future outcomes, Surprise is a determinant of a team dismissing their Head Coach. This is a point we come to during our discussions on covariate balancing.

[12]Note that this period covers a number of match fixing scandals, perhaps most notably is the *Calciopoli* scandal in Italian football. We tested the robustness of our results to excluding the five implicated teams between 2004–05 and 2005–06 (totalling 380 observations). Results were identical. Other scandals were primarily centred on minor European leagues not in our dataset. Outside of *Calciopoli*, only four games covered by our sample in the German second division were investigated by authorities, and thus our results (comprising almost 65,000 matches) would be unaffected.

skewness of the covariate distributions for the control group get much closer (even identical in some cases) to the treated group once weights have been introduced.[13]

The covariates we balance on are all variables that, at least in theory, should predict head coach departures over the 10 game period before any turnover event takes place. We follow Bryson et al. (2020) in our selection of covariates that affect departures. These capture a combination of team form, coaching characteristics and season progress. For an analysis of variables that are associated with both types of turnover, see Table A5 in the Appendix, which displays the results of a multinomial logit regression predicting both quits and dismissals. Team form variables include mean points per game over the last 10 games, league position (where position is captured as rank across both tiers per country) and the final league position of the team in the previous season. These variables enter with the anticipated sign. Since owners' (and stakeholders') expectations about performance (as well as actual performance) are likely to play a role in coaching departures, we also include lagged cumulative surprise, as discussed earlier. Should performance slip below some acceptable level in the eyes of the principal, which will include knowledge about opponent quality, then the team may look to replace the head coach (Van Ours & Van Tuijl, 2016). A negative Surprise value is a likely signal of a poorly performing head coach. The results in Table A5 show that more recent runs of good or bad form are far more important in explaining turnovers.

Our measures of (incumbent) head coach characteristics include tenure at the current team (measured in number of games coached), experience (years since first coaching job), age and its square, the number of previous head coach spells, dummy variables capturing previous successes and failures as a coach (previous promotions, previous cup winners and a previous relegation), and dummy variables capturing some kind of connection with the club, namely, whether the coach was hired from within and whether the coach is an ex-player at the club. The latter two variables, along with tenure, can be thought of as club-specific measures of human capital, while the other measures capture more general human capital that is skills and or experiences that are not specific to any one club. Measures of previous success appear to offer some protective effect against dismissals, as does being an ex-player, even when controlling for performance. Finally, our measures of season progress (in line with Figure 1) include the proportion of games remaining (to account for differences in season length) and whether the departure occurred after the last game of the season. These variables reflect the patterns of departures as shown in Figure 1. Descriptive statistics of our covariates and selected outcomes are shown in Table 2.

Entropy Balancing has several advantages, both in a practical and an econometric sense, over more conventional weighting and matching methods (such as Inverse Probability Weighting Regression Adjustment or Propensity Score Matching). From the researcher's point of view, the scheme removes the need for the continual iterative process of running a propensity score model and checking for covariate balance, not to mention the concern of mis-specifying the treatment model. Instead, entropy balancing directly achieves covariate balance via the weighting procedure, rather than via a manual process which is unlikely to achieve balance on all covariates (Hainmueller & Xu, 2013; Krishnan & Krutikova, 2013). Zhao and Percival (2017) also show that entropy balancing possesses the attractive property of being doubly robust, even though no treatment model is actually estimated, while also producing treatment effects that are within the range of observed outcomes.

Our preferred variants of the entropy balanced models include team fixed effects, thus focusing on comparisons of team performance within team over time. In doing so, we avoid biases in estimates of head coach departures arising from fixed unobservable differences across teams. Our baseline models compare spells ending in either a head coach quit or dismissal (which occur at time $t=0$), relative to counterfactual spells which did not end in a head coach departure, where we follow subsequent performance up to a maximum of a further 20 game period ($t=1$ to $t=20$), regardless of whether there are subsequent head coach changes in the period after $t=0$. For the control group, $t=0$ is simply the midpoint of any spell not ending in a turnover

[13]Note also that our unweighted OLS estimates can be found in Appendix Tables A3 and A4.

TABLE 2 Descriptive statistics.

Variable	Obs	Mean	SD	Min	Max
Outcomes[a]					
Mean points per game next 1 game	65,998	1.391	1.293	0	3
Mean points per game next 5 games	65,339	1.390	0.620	0	3
Mean points per game next 10 games	64,494	1.391	0.481	0	3
Mean points per game next 15 games	63,626	1.391	0.423	0.133	3
Mean points per game next 20 games	62,751	1.391	0.390	0.150	2.900
Team performance					
Surprise $t-1$	66,157	0.014	1.198	−2.707	2.797
Surprise $t-2$ to $t-5$	66,157	0.061	2.371	−8.269	8.277
Surprise $t-6$ to $t-10$	66,157	0.080	2.649	−9.681	9.760
Mean points per game prev 10 games	66,157	1.395	0.479	0	3
Position	66,157	19.927	12.524	1	48
Last season position	66,157	28.377	21.872	1	66
Coach characteristics					
Tenure (*n* games)	66,157	44.653	47.062	1	441
Experience (years)	66,157	11.475	7.707	0	44
Age	66,157	48.439	6.582	30.212	73.739
N prev HC jobs	66,157	4.395	3.888	0	23
Previous promotion	66,157	0.525	0.499	0	1
Previous cup	66,157	0.195	0.397	0	1
Previous relegation	66,157	0.268	0.443	0	1
Internal	66,157	0.138	0.345	0	1
Ex player	66,157	0.160	0.366	0	1
Season progress					
Proportion of games remaining	66,157	0.484	0.285	0	0.978
Last game of season	66,157	0.025	0.155	0	1

[a]The number of observations for our outcome variables decreases as we expand on the number of games for our follow-up spell because our sample period ends at the 14/15 season, and so do not observe games at the start of the 15/16 season.

event. We also run separate models with the inclusion of season fixed effects, thus capturing season specific variations in performances.

It is arguable that football results should count when estimating the impact of a coach dismissal or quit, even if there is subsequent coach turnover in the outcome spell. In a later analysis, however, we test the sensitivity of this definition by restricting our analyses to a subset of 'clean' spells, which we define as a series of games where no subsequent head coach change occurs. While this facilitates an assessment of the longer-term performance of the initial head coach change where that performance is permitted to develop, the approach is not without its pitfalls. It is arguable that in dropping spells with a subsequent head coach change, we are truncating the sample based on a potentially endogenous variable that is whether team owners choose to retain the coach for another 20 games, since this will partly reflect how well the new head coach is performing during that period. Nevertheless, the results are interesting in that they are likely to capture an upper bound of the effect of changing head coach.

4 | RESULTS

4.1 | Baseline entropy balance models

We start by presenting our baseline estimates, using the entropy balanced weights as specified by the Stata routine in a weighted version of Equation (1).[14] Table 3 displays the results for dismissals, while Table 4 displays the results for quits. Each coefficient is the result of a separate regression, which models points per game over the next 1 through 20 games. Both sets of results suggest that team performance does not significantly improve for any sustained run of games following either a dismissal or a quit. Considering models with no fixed effects in column (1), the only coefficient to display any significance is 3 games after a dismissal. That is, 3 games after a dismissal, teams are obtaining 0.048 points per game (or roughly 0.144 total points) more than teams who did not dismiss their coach having experienced similar runs of form. Though this result is only significant at the 10% level. The effect of including of team fixed effects in column (2) is to reduce the magnitude of the point estimates. In fact, 9 games after a dismissal, there is now limited evidence to suggest that teams actually perform worse after a dismissal (0.031 points per game fewer, though again, only significant at 10%). Including team fixed effects means we are relying on spells of games within team to obtain our counterfactual spells. If these omitted differences are correlated with the tendency to change coaches, then the estimates without team fixed effects will be biased, with the team fixed effects soaking up a great deal of the across team differences. In practical terms, any positive effects of a coaching change may be limited to a select number of teams. The effect of including season fixed in column (3) effects is negligible, with our coefficient estimates on points per game very closely resembling those when not included.

Of course, these are all average effects, but within that average will lie a range of outcomes, with some teams benefitting from changing their coach, others will indeed experience no effects, while others will likely suffer worsening results. Of course, this begs the question why would teams make a head coach change even if they know the average effect is negligible. They may be attracted by the small probability of a successful coach change, or may even overestimate the small probability of the turnover resulting in a change of fortunes (e.g. Prelec, 1998, also see Barberis, 2013 for a range of applications of probability weighting). On the other hand, this zero average effect is consistent with several ideas from the sports literature, including the scapegoat hypothesis of fan disgruntlement and pressure (e.g. Tena & Forrest, 2007), in that a change is made simply to appease disgruntled fans, even though performance is unlikely to improve, as well as mediocre talent (Peeters et al., 2022; Terviö, 2009). In what follows, we attempt to uncover a possible upper bound of the effect of a head coach turnover.

4.2 | Sensitivity analysis

4.2.1 | 'Clean' follow-up spells

As noted earlier, we define a 'clean' follow-up spell as one where no subsequent coaching change occurs after the initial change at $t = 0$ up to $t = 20$. In other words, we are considering the subsample of teams who stick with their new coach. Given the limitations of this approach outlined in Section 3, these models are likely capturing an upper bound of the effects of a head coach change, since we are considering spells where performance is permitted to develop. Under this definition, both quits and dismissals now show evidence of positive returns after changing a Head Coach (Tables 5 and 6).[15] In the team fixed effect models in column 2, positive performance effects following a dismissal are apparent after around 10 games as well as an initial 'bump' effect at

[14]Note also that our unweighted OLS regressions (Appendix Tables A3 and A4) demonstrate very little evidence of performance changes following either a dismissal or a quit.

[15]Spells that last 20 games or fewer represents a fairly sizeable portion of our data. 34% of head coach spells are over by or on the 20th game. Over 13% of coaches do not even last until the 10th game. These short spells are predominantly occurring in Italy and Spain.

TABLE 3 Entropy balanced OLS (dismissals).

Mean points per game next ... games	(1) Coeff	(1) SE	(2) Coeff	(2) SE	(3) Coeff	(3) SE	N	Adj.R^2 (no FE)	Adj.R^2 (team FE)	Adj.R^2 (season FE)
1	−0.008	(0.043)	0.011	(0.045)	−0.016	(0.042)	65,603	0.084	0.144	0.089
2	0.032	(0.033)	0.028	(0.035)	0.030	(0.033)	65,440	0.056	0.112	0.061
3	0.048*	(0.028)	0.039	(0.030)	0.047*	(0.028)	65,275	0.074	0.137	0.079
4	0.038	(0.025)	0.028	(0.026)	0.037	(0.025)	65,110	0.073	0.143	0.078
5	0.015	(0.022)	0.005	(0.023)	0.014	(0.022)	64,944	0.086	0.160	0.090
6	0.004	(0.021)	−0.007	(0.021)	0.003	(0.020)	64,778	0.092	0.181	0.096
7	−0.007	(0.019)	−0.021	(0.019)	−0.008	(0.019)	64,612	0.100	0.198	0.106
8	−0.006	(0.019)	−0.019	(0.018)	−0.006	(0.018)	64,443	0.103	0.210	0.107
9	−0.015	(0.018)	−0.031*	(0.018)	−0.014	(0.018)	64,273	0.109	0.227	0.114
10	−0.002	(0.017)	−0.019	(0.016)	−0.001	(0.017)	64,101	0.124	0.242	0.129
11	−0.002	(0.016)	−0.016	(0.015)	−0.001	(0.016)	63,929	0.127	0.256	0.132
12	−0.006	(0.016)	−0.021	(0.014)	−0.006	(0.016)	63,755	0.134	0.269	0.139
13	0.001	(0.015)	−0.013	(0.013)	0.001	(0.015)	63,582	0.134	0.283	0.140
14	0.005	(0.015)	−0.009	(0.013)	0.005	(0.015)	63,409	0.145	0.298	0.152
15	0.005	(0.015)	−0.009	(0.013)	0.005	(0.015)	63,235	0.147	0.312	0.154
16	0.006	(0.015)	−0.009	(0.013)	0.006	(0.015)	63,059	0.147	0.320	0.155
17	0.011	(0.015)	−0.004	(0.012)	0.011	(0.014)	62,885	0.153	0.327	0.160
18	0.011	(0.014)	−0.006	(0.012)	0.011	(0.014)	62,711	0.154	0.333	0.162
19	0.017	(0.014)	0.000	(0.011)	0.017	(0.014)	62,535	0.155	0.342	0.163
20	0.016	(0.014)	−0.002	(0.011)	0.017	(0.014)	62,360	0.154	0.352	0.162
Fixed effects	None		Team		Season					

Note: Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent n games for teams who dismissed their coach, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).
***$p<0.01$; **$p<0.05$; *$p<0.1$.

games 3–4, a pattern that is more consistent with the predictions outlined in Section 2.3. That is, an initial effect attributable to simply making a change, followed by a period of learning on the job to improve one's effectiveness, before results improve in the longer run. Taking the coefficient of 0.075 from the 20 game, team FE dismissals model, this would indicate that teams can expect to be, on average, 1.5 points better off 20 games after a coach dismissal. Unexpectedly, there is also some evidence of improvements in performance after a coach quits, although these take some time to emerge in the team fixed effects models. Practically speaking, this sensitivity analysis highlights the importance of finding a good job match with the initial hire. There is no official interview process that teams must go through, and teams often have a new appointment lined up even before they have dismissed the incumbent coach. Without taking the time to interview and carefully select candidates, it is possible that the wrong hire is made with a low-job match surplus, only to be dismissed a few games later.

4.2.2 | Promotions and relegations

We consider the role of promotions and relegations in our estimations, by removing the games from the season immediately following one of these events. Results tables can be found in the Appendix, Tables A6 and A7. Results

TABLE 4 Entropy balanced OLS (quits).

Mean points per game next … games	(1) Coeff	(1) SE	(2) Coeff	(2) SE	(3) Coeff	(3) SE	N	Adj.R^2 (no FE)	Adj.R^2 (team FE)	Adj.R^2 (season FE)
1	0.020	(0.066)	−0.031	(0.073)	0.022	(0.067)	65,048	0.152	0.281	0.157
2	−0.002	(0.050)	−0.008	(0.054)	−0.007	(0.050)	64,888	0.092	0.232	0.100
3	0.023	(0.048)	0.011	(0.051)	0.019	(0.048)	64,725	0.100	0.253	0.103
4	0.004	(0.042)	0.000	(0.043)	0.004	(0.042)	64,561	0.105	0.269	0.110
5	0.003	(0.038)	−0.010	(0.039)	0.005	(0.039)	64,396	0.113	0.279	0.117
6	0.016	(0.035)	0.005	(0.036)	0.016	(0.036)	64,232	0.116	0.301	0.119
7	0.017	(0.033)	0.003	(0.033)	0.017	(0.033)	64,069	0.126	0.326	0.130
8	0.012	(0.031)	−0.002	(0.031)	0.011	(0.032)	63,902	0.138	0.361	0.141
9	0.006	(0.030)	−0.013	(0.030)	0.006	(0.030)	63,736	0.141	0.367	0.145
10	0.000	(0.029)	−0.020	(0.029)	0.000	(0.029)	63,569	0.161	0.398	0.165
11	−0.009	(0.028)	−0.032	(0.027)	−0.008	(0.028)	63,398	0.166	0.408	0.171
12	−0.003	(0.026)	−0.024	(0.025)	−0.001	(0.026)	63,228	0.178	0.423	0.183
13	0.004	(0.026)	−0.019	(0.025)	0.006	(0.026)	63,058	0.183	0.435	0.189
14	0.005	(0.025)	−0.018	(0.024)	0.006	(0.025)	62,888	0.197	0.452	0.203
15	−0.003	(0.024)	−0.022	(0.023)	−0.002	(0.024)	62,714	0.198	0.452	0.202
16	−0.003	(0.023)	−0.022	(0.023)	−0.002	(0.023)	62,542	0.205	0.460	0.209
17	−0.008	(0.023)	−0.025	(0.022)	−0.008	(0.023)	62,371	0.210	0.470	0.214
18	−0.006	(0.022)	−0.018	(0.021)	−0.005	(0.022)	62,200	0.224	0.481	0.228
19	−0.010	(0.022)	−0.022	(0.021)	−0.008	(0.022)	62,030	0.228	0.489	0.232
20	−0.008	(0.021)	−0.022	(0.020)	−0.006	(0.021)	61,856	0.228	0.498	0.233
Fixed effects	None		Team		Season					

Note: Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent *n* games for teams whose coach quit their post, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).
***$p<0.01$; **$p<0.05$; *$p<0.1$.

are largely unchanged from our baseline specification, though the team fixed effects variant of our dismissals model when taking out promoted teams shows some evidence of a bump to performance early in the new coach's tenure. By excluding newly promoted teams, who are likely to be lower in the table and perhaps struggling to adapt to the higher division, a new coach may find it harder to have any impact on results. Hence, we see this ‘bump’ emerge when excluding these newly promoted teams.

4.2.3 | Further checks

Finally, we consider the results of two further robustness checks (full results for both of these can be made available on request).

We first test whether the effect of head coach turnover differs across different ‘brackets’ of teams within the league. In particular, we define top teams, mid teams and low teams (which roughly corresponds to thirds of the leagues), according to a team's position in the league when the coaching change was made. Top teams would be those competing for the league title and European football, or promotion (depending on the division), while low

TABLE 5 Entropy balanced OLS (dismissals) with a clean follow-up spell.

Mean points per game next ... games	(1) Coeff	(1) SE	(2) Coeff	(2) SE	(3) Coeff	(3) SE	N	Adj.R^2 (no FE)	Adj.R^2 (team FE)	Adj.R^2 (season FE)
1	0.013	(0.044)	0.051	(0.045)	0.003	(0.043)	65,461	0.085	0.139	0.090
2	0.054	(0.034)	0.058	(0.035)	0.051	(0.034)	65,297	0.052	0.107	0.055
3	0.064**	(0.028)	0.056*	(0.030)	0.062**	(0.029)	65,131	0.071	0.133	0.073
4	0.071***	(0.025)	0.057**	(0.027)	0.070***	(0.025)	64,956	0.069	0.138	0.074
5	0.056**	(0.022)	0.036	(0.023)	0.055**	(0.022)	64,783	0.084	0.158	0.088
6	0.046**	(0.021)	0.024	(0.022)	0.045**	(0.021)	64,609	0.088	0.179	0.091
7	0.042**	(0.020)	0.019	(0.020)	0.042**	(0.020)	64,428	0.096	0.196	0.100
8	0.041**	(0.020)	0.016	(0.019)	0.041**	(0.020)	64,253	0.101	0.208	0.104
9	0.039**	(0.019)	0.009	(0.019)	0.039**	(0.019)	64,069	0.108	0.229	0.112
10	0.056***	(0.018)	0.030*	(0.017)	0.056***	(0.018)	63,880	0.127	0.255	0.132
11	0.061***	(0.018)	0.036**	(0.016)	0.062***	(0.018)	63,684	0.132	0.270	0.137
12	0.059***	(0.018)	0.031*	(0.016)	0.059***	(0.018)	63,494	0.142	0.285	0.147
13	0.066***	(0.017)	0.039***	(0.015)	0.066***	(0.017)	63,312	0.147	0.302	0.152
14	0.072***	(0.017)	0.045***	(0.014)	0.071***	(0.017)	63,128	0.157	0.315	0.162
15	0.081***	(0.017)	0.051***	(0.015)	0.080***	(0.017)	62,933	0.165	0.332	0.170
16	0.080***	(0.017)	0.050***	(0.014)	0.080***	(0.017)	62,743	0.165	0.339	0.172
17	0.091***	(0.017)	0.060***	(0.014)	0.090***	(0.017)	62,551	0.172	0.349	0.178
18	0.097***	(0.016)	0.063***	(0.013)	0.096***	(0.016)	62,364	0.180	0.360	0.187
19	0.110***	(0.016)	0.073***	(0.013)	0.109***	(0.016)	62,172	0.186	0.372	0.193
20	0.112***	(0.015)	0.075***	(0.012)	0.112***	(0.015)	61,980	0.189	0.383	0.195
Fixed effects	None		Team		Season					

Note: Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent n games for teams who dismissed their coach and experienced no further coaching turnover in the 20 game spell, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).
***$p<0.01$; **$p<0.05$; *$p<0.1$.

teams would be fighting to avoid relegation. Effects might differ due to different talents of playing squads, different budgets available and different owner objectives. In short, the results demonstrate that, regardless of whether a team is classed as a top, mid or low team, those who dismiss their coach fail to gain any performance advantage over similarly placed teams with similar pre-treatment characteristics, but did not dismiss their coach. Interestingly however, when a coach quits from a mid-table team, they experience a sustained negative impact on performance throughout the entire 20 game spell. While further investigation would be required as to why this may be the case, it could be indicative of poaching coaches from overperforming mid table clubs, with these clubs then failing to adequately replace the coach, hence, suffering a downturn in performance.[16]

Finally, we test whether the point at which a team experiences a coaching turnover matters. For dismissals in particular, the objectives of the owner could be quite different depending on when in the season a coaching

[16]On a related note, to this point all of our estimations have used points per game as the outcome of interest. We believe this is appropriate since all possible objectives (promotion, European qualification, avoiding relegation, etc.) ultimately depend on winning points. With that said, the same number of accumulated points can result in different end-of-season outcomes as this will depend on the initial number of points at the time of appointment. Hence, as a cursory check, we also estimated a linear probability model with being relegated at the end of the season as an outcome. The results from these models (available on request) show that coach turnover, of either type, are insignificant predictor of relegation.

TABLE 6 Entropy balanced OLS (quits) with a clean follow up spell.

Mean points per game next ... games	(1) Coeff	SE	(2) Coeff	SE	(3) Coeff	SE	N	Adj.R^2 (no FE)	Adj.R^2 (team FE)	Adj.R^2 (season FE)
1	0.043	(0.070)	−0.005	(0.077)	0.048	(0.071)	65,003	0.147	0.274	0.154
2	0.028	(0.053)	0.028	(0.057)	0.023	(0.052)	64,842	0.088	0.229	0.098
3	0.057	(0.049)	0.050	(0.053)	0.056	(0.049)	64,679	0.095	0.251	0.099
4	0.029	(0.043)	0.026	(0.044)	0.031	(0.043)	64,512	0.094	0.265	0.099
5	0.038	(0.040)	0.029	(0.041)	0.042	(0.040)	64,343	0.107	0.287	0.112
6	0.041	(0.038)	0.032	(0.037)	0.044	(0.038)	64,178	0.109	0.310	0.114
7	0.036	(0.035)	0.022	(0.034)	0.038	(0.035)	64,011	0.122	0.331	0.128
8	0.036	(0.033)	0.024	(0.033)	0.038	(0.034)	63,841	0.133	0.360	0.137
9	0.037	(0.032)	0.018	(0.032)	0.040	(0.032)	63,671	0.134	0.375	0.140
10	0.024	(0.031)	0.003	(0.030)	0.026	(0.031)	63,503	0.152	0.399	0.157
11	0.030	(0.029)	0.003	(0.029)	0.031	(0.029)	63,326	0.166	0.409	0.172
12	0.037	(0.027)	0.008	(0.026)	0.038	(0.027)	63,151	0.176	0.419	0.181
13	0.053*	(0.027)	0.020	(0.026)	0.055**	(0.028)	62,974	0.183	0.428	0.188
14	0.064**	(0.026)	0.027	(0.025)	0.064**	(0.027)	62,797	0.199	0.447	0.204
15	0.053**	(0.026)	0.023	(0.024)	0.054**	(0.026)	62,619	0.198	0.448	0.201
16	0.064**	(0.025)	0.031	(0.024)	0.065**	(0.025)	62,439	0.203	0.455	0.205
17	0.064**	(0.025)	0.035	(0.024)	0.064**	(0.025)	62,260	0.211	0.466	0.213
18	0.080***	(0.024)	0.050**	(0.023)	0.080***	(0.025)	62,080	0.232	0.476	0.234
19	0.085***	(0.025)	0.055**	(0.023)	0.085***	(0.025)	61,902	0.238	0.493	0.240
20	0.091***	(0.024)	0.061***	(0.022)	0.091***	(0.024)	61,722	0.238	0.501	0.240
Fixed effects	None		Team		Season					

Note: Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent n games for teams whose coach quit their post and experienced no further coaching turnover in the 20 game spell, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

change was made. We would hypothesise that dismissals made towards the end of the season might be more aimed at short term improvements as teams seek to achieve a particular objective (e.g. qualifying for European football, avoiding relegation, etc.), while dismissals at the start of the season might be aimed at bringing longer term improvements. The effect of a quit is less clear. Nevertheless, when we split the sample into early turnovers (defined as August–December) and late turnovers (January–May), our results remain remarkably similar to initial results in Tables 3–6. One comment about splitting the sample in such a way is that it becomes harder to evaluate longer follow up spells for turnovers occurring in March, April and May, as these spells of games become increasingly reliant on games taking place in the following season.

5 | CONCLUSIONS

Using a large, linked employer–employee data set for professional football in four countries, we are able to separate out the a priori theoretically different effects on performance of a coach being dismissed and a coach quitting. The professional football setting is useful in trying to isolate the causal impact of leadership on organisational performance, partly because the industry does not usually suffer from the exogenous shocks that afflict many other industries which make it harder to attribute performance change to management. The setting also means principals who hire and fire their managers - head coaches in this setting - benefit from quick and frequent updating of firm performance because football teams tend to play one or two games per week during the football season.

Even though there is a strong theoretical argument to suggest that leadership changes in football could, and perhaps should make a difference, our estimates using entropy balancing fail to show any consistent gains to performance following either a dismissal or a quit, when compared to unconstrained counterfactual scenarios in which teams suffer similar runs of form but do not immediately experience head coach turnover. The finding is largely in keeping with other studies which suggest regression to the mean can explain the lack of sustained positive effects of head coach changes on football team performance.

As an attempt to delve into this zero average effect, we estimate what is likely to be an upper bound of the effect of managerial change by constraining our results to spells where performance is permitted to develop and examining the effects of a coach change among teams who make no subsequent coaching change in the 20 games after the initial change. Using these constrained spells, we find teams can experience positive returns after a dismissal of between 0.04 and 0.1 points per game, and between 0.05 and 0.09 points per game after a quit, with the effects for quits occurring later in the follow-up spell (notwithstanding the difficulty in interpreting this as a causal effect as discussed). Even though the magnitude is rather small in a sporting sense, this could well prove the difference between relegation and staying up, or qualifying for a European competition or not, which are undoubted signs of success. That is not to say that teams should keep hold of their new coach regardless of results. Instead, we believe this finding highlights the importance of a finding good job match in the first place, rather than continually changing coaches.

Our baseline findings of insignificant effects on team performance following head coach turnover are more consistent with previous research in this area and theories of scapegoating and mediocre (and/or homogenous) talent, than with economic theory as laid out by Farber (1999). The latter would suggest that since dismissals are triggered by principals (team owners) rather than agents (employed coaches), owners can use their acquired information on the head coach's ability and productivity to terminate the relationship with the aim of securing a better job match with a new hire. Quits are triggered by the agent, rather than the principal, with the departing coach seeking better opportunities elsewhere (which include switching to a different job as well as different employer). Given that the job match was satisfactory to the employer (team owner) without consideration of the coach's outside options then the best the employer can do is to replace the coach with a job match that is just as good as the previous one. Nevertheless, our results show that team performance, on average, is neither improved nor impaired by head coach succession following either a dismissal or a quit, at least not over a 20-game period, suggesting that job matches between teams and voluntarily departing coaches were, on average, efficient.

We note as a point for further research that our results do not entirely support the conjecture of a market for mediocre managerial talent advanced by Terviö (2009) and Peeters et al. (2022). If most coaches were mediocre then we would not observe any positive effects on team performance that we find from cases of fired coaches in our sensitivity analysis. It is possible that a head coach who appears mediocre at one club can be successful at another. Put another way, the value of a job match varies across clubs and each club has an idiosyncratic element in this value. A poorly performing club will tend to draw its hiring from the lower end of the ability distribution but such a coach can nevertheless help improve team performance.

Our work leaves the door open for a number of potential avenues for further work. Primarily, further investigation is needed to investigate heterogeneity of head coach effects on team performance, since coaches themselves are likely to be heterogeneous in ability (Peeters et al., 2022). Even if our estimates, and indeed estimates of past work, yield low or zero mean effects, there may well be some positive, some zero and some negative effects and it is worth probing into where and how these occur and whether there are systematic patterns to the positive and negative effects. We have already illustrated some instances where heterogeneity may exist. Moreover, throughout the work we have spoken about the difference between a British football *manager*, and the continental style *head* *coach*. This is a difference which we also feel merits investigation, which may also align with how different ownership structures affect a coach's ability to make an impact. Another avenue could be to explore differences between countries, where different labour market customs may exist to limit or enhance the effect of any incoming head coach.

Finally, it is natural to ask to what extent these findings can be applied to managers in other industries? On the one hand, Pieper et al. (2014) point out many similarities between football head coaches and leaders of organisations more broadly. Namely, they are (predominantly) male, are typically in their late 40's and 50's, can deal with intense scrutiny, and ultimately report to a supervisory body (i.e. owners and directors) who decide upon their contract continuation or otherwise. These similarities in personal characteristics and organisational hierarchy, along with the particular conditions associated with inefficient talent discovery as laid out by Terviö (2009), might mean there is scope to interpret our results more broadly. Moreover, non-sporting organisations may also use job/managerial rotations as a way of improving their performance (Muehlheusser et al., 2016). Yet, there are of course clear differences between the football industry and other settings. Most of all is that football team performance is more readily and frequently observed. Our results capture performance changes over a fairly frequent timeframe, but it is not clear how other industries would get an opportunity to observe managerial performance on such a regular basis. Nevertheless, even taken in isolation these findings still speak to the football industry (and perhaps sports more generally); an industry where coaching/leadership changes are frequent, but apparently have little effect on team performance.

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APPENDIX A

TABLE A1 Entropy balancing (dismissals).

	Mean			Variance			Skewness		
	Unweighted	Unweighted	Weighted	Unweighted	Unweighted	Weighted	Unweighted	Unweighted	Weighted
	Treatment	Control	Control	Treatment	Control	Control	Treatment	Control	Control
Surprise $t-1$	−0.4482	0.02179	−0.4481	1.076	1.438	1.075	0.9632	0.251	0.9632
Surprise $t-2$ to $t-5$	−1.097	0.08274	−1.097	4.764	5.618	4.763	0.4275	0.1144	0.4274
Surprise $t-6$ to $t-10$	−0.7296	0.09391	−0.7296	5.765	7.024	5.764	0.3676	0.09937	0.3675
Mean points prev 10 games	1.069	1.401	1.069	0.1722	0.228	0.1722	0.5912	0.2315	0.5919
Position	17.1	19.99	17.09	162.7	156.6	162.7	0.2108	0.2828	0.2119
Position squared	454.8	556	454.8	238,663	315,283	238,643	0.954	0.8982	0.9542
Last season position	30.08	28.36	30.08	516.1	477.8	516.1	0.1102	0.2905	0.1105
Tenure	38.85	44.61	38.85	1126	2225	1125	1.903	2.696	1.903
Experience	11.46	11.47	11.45	63.38	59.25	63.37	0.7147	0.7602	0.7151
Age	49.22	48.42	49.21	45.65	43.21	45.65	0.3663	0.3959	0.3677
Age squared	2468	2388	2468	468,590	430,630	468,551	0.7298	0.754	0.731
N prev HC jobs	4.877	4.385	4.876	17.82	15.06	17.82	1.16	1.283	1.16
Internal appointment	0.1367	0.1386	0.1369	0.1181	0.1194	0.1181	2.115	2.092	2.113
Previous promotion	0.4981	0.5254	0.4981	0.2502	0.2494	0.25	0.007648	−0.1016	0.007628
Previous cup	0.1396	0.1959	0.1398	0.1202	0.1575	0.1202	2.08	1.532	2.078
Previous relegation	0.3184	0.2678	0.3186	0.2172	0.1961	0.2171	0.7799	1.049	0.7785
Ex player	0.1338	0.1604	0.134	0.116	0.1347	0.1161	2.151	1.851	2.149
Proportion of games remaining	0.3355	0.489	0.3354	0.09008	0.07989	0.09007	0.2687	0.01582	0.2694
Proportion of games remaining squared	0.2025	0.319	0.2026	0.0559	0.08237	0.05589	1.044	0.6702	1.043
Last game of season	0.3193	0.01488	0.3196	0.2176	0.01465	0.2175	0.7751	8.015	0.7738

Note: The table shows the moments of the covariate distributions across treated and control groups, for cases where treatment is coach dismissal.

TABLE A2 Entropy balancing (quits).

	Mean			Variance			Skewness		
	Unweighted Treatment	Unweighted Control	Weighted Control	Unweighted Treatment	Unweighted Control	Weighted Control	Unweighted Treatment	Unweighted Control	Weighted Control
Surprise $t-1$	−0.08757	0.02179	−0.08753	1.379	1.438	1.378	0.415	0.251	0.4149
Surprise $t-2$ to $t-5$	−0.3931	0.08274	−0.3929	4.969	5.618	4.968	0.2405	0.1144	0.2404
Surprise $t-6$ to $t-10$	−0.08577	0.09391	−0.08579	7.511	7.024	7.508	0.2257	0.09937	0.2257
Mean points prev 10 games	1.319	1.401	1.319	0.2627	0.228	0.2626	0.4913	0.2315	0.4937
Position	18.06	19.99	18.05	156.4	156.6	156.4	0.4881	0.2828	0.4909
Position squared	482.2	556	482.1	296,922	315,283	296,846	1.095	0.8982	1.096
Last season position	27.29	28.36	27.29	468.7	477.8	468.5	0.4341	0.2905	0.4353
Tenure	64.29	44.61	64.26	2925	2225	2924	2.58	2.696	2.581
Experience	12.58	11.47	12.58	71.22	59.25	71.2	0.826	0.7602	0.8274
Age	49.44	48.42	49.43	51.95	43.21	51.94	0.5006	0.3959	0.5055
Age squared	2496	2388	2495	549,883	430,630	549,779	0.8332	0.754	0.8376
N prev HC jobs	4.797	4.385	4.795	17.23	15.06	17.23	1.202	1.283	1.203
Internal appointment	0.1038	0.1386	0.1041	0.09327	0.1194	0.09328	2.597	2.092	2.592
Previous promotion	0.5598	0.5254	0.5595	0.247	0.2494	0.2465	−0.241	−0.1016	−0.2396
Previous cup	0.2506	0.1959	0.2512	0.1882	0.1575	0.1881	1.151	1.532	1.148
Previous relegation	0.2415	0.2678	0.2421	0.1836	0.1961	0.1835	1.208	1.049	1.204
Ex player	0.1264	0.1604	0.1268	0.1107	0.1347	0.1107	2.248	1.851	2.243
Proportion of games remaining	0.1039	0.489	0.1037	0.05434	0.07989	0.05444	2.195	0.01582	2.2
Proportion of games remaining squared	0.06501	0.319	0.06519	0.03024	0.08237	0.03035	3.003	0.6702	3.001
Last game of season	0.772	0.01488	0.771	0.1764	0.01465	0.1765	−1.297	8.015	−1.29

Note: The table shows the moments of the covariate distributions across treated and control groups, for cases where treatment is a coach quitting.

TABLE A3 Unweighted OLS estimates (dismissals).

Mean points per game next … games	(1) Coeff	SE	(2) Coeff	SE	(3) Coeff	SE	N	Adj.R^2 (no FE)	Adj.R^2 (team FE)	Adj.R^2 (season FE)
1	−0.007	(0.037)	0.002	(0.038)	−0.007	(0.037)	74,718	0.107	0.118	0.107
2	0.035	(0.027)	0.038	(0.027)	0.035	(0.027)	74,516	0.082	0.089	0.082
3	0.040*	(0.022)	0.036*	(0.022)	0.040*	(0.022)	74,311	0.110	0.118	0.110
4	0.030	(0.019)	0.023	(0.019)	0.031	(0.019)	74,106	0.121	0.134	0.122
5	0.012	(0.017)	0.001	(0.017)	0.012	(0.017)	73,901	0.141	0.159	0.141
6	0.005	(0.016)	−0.008	(0.015)	0.005	(0.016)	73,697	0.154	0.179	0.155
7	−0.001	(0.015)	−0.016	(0.015)	−0.001	(0.015)	73,493	0.170	0.200	0.170
8	0.002	(0.014)	−0.014	(0.014)	0.002	(0.014)	73,286	0.183	0.219	0.183
9	−0.006	(0.014)	−0.022*	(0.013)	−0.005	(0.014)	73,078	0.196	0.238	0.196
10	0.002	(0.013)	−0.015	(0.012)	0.003	(0.013)	72,869	0.208	0.256	0.208
11	0.005	(0.012)	−0.013	(0.012)	0.005	(0.012)	72,661	0.218	0.272	0.219
12	0.002	(0.012)	−0.018	(0.011)	0.002	(0.012)	72,454	0.228	0.287	0.229
13	0.007	(0.012)	−0.012	(0.011)	0.008	(0.012)	72,246	0.237	0.301	0.238
14	0.009	(0.011)	−0.011	(0.010)	0.010	(0.011)	72,039	0.245	0.314	0.245
15	0.013	(0.012)	−0.008	(0.010)	0.014	(0.012)	71,831	0.251	0.326	0.251
16	0.014	(0.011)	−0.007	(0.010)	0.015	(0.011)	71,624	0.257	0.337	0.257
17	0.019	(0.011)	−0.004	(0.010)	0.019*	(0.011)	71,418	0.261	0.348	0.262
18	0.020*	(0.011)	−0.003	(0.010)	0.020*	(0.011)	71,213	0.265	0.357	0.266
19	0.026**	(0.011)	0.003	(0.010)	0.026**	(0.011)	71,007	0.268	0.365	0.269
20	0.026**	(0.011)	0.002	(0.010)	0.026**	(0.011)	70,803	0.270	0.373	0.271
Fixed effects	None		Team		Season					

Note: Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent *n* games for teams who dismissed their coach, over and above teams who experience no coaching turnover. Models contain no balancing weights. Cluster robust standard errors in parentheses (clustered at the team level).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A4 Unweighted OLS estimates (quits).

Mean points per game next ... games	(1) Coeff	(1) SE	(2) Coeff	(2) SE	(3) Coeff	(3) SE	N	Adj.R^2 (no FE)	Adj.R^2 (team FE)	Adj.R^2 (season FE)
1	−0.058	(0.047)	−0.077*	(0.046)	−0.059	(0.047)	74,038	0.107	0.118	0.107
2	−0.045	(0.039)	−0.050	(0.039)	−0.046	(0.039)	73,840	0.082	0.089	0.082
3	−0.025	(0.036)	−0.028	(0.036)	−0.026	(0.036)	73,637	0.111	0.119	0.111
4	−0.022	(0.030)	−0.024	(0.030)	−0.023	(0.030)	73,433	0.122	0.134	0.122
5	−0.020	(0.028)	−0.022	(0.027)	−0.021	(0.028)	73,229	0.142	0.159	0.142
6	−0.003	(0.026)	−0.004	(0.026)	−0.004	(0.026)	73,027	0.155	0.179	0.155
7	0.004	(0.026)	0.003	(0.025)	0.003	(0.026)	72,827	0.170	0.200	0.170
8	−0.001	(0.026)	−0.002	(0.026)	−0.001	(0.026)	72,623	0.183	0.220	0.183
9	−0.001	(0.024)	−0.003	(0.024)	−0.002	(0.024)	72,419	0.196	0.239	0.196
10	−0.010	(0.024)	−0.013	(0.023)	−0.011	(0.024)	72,217	0.208	0.256	0.208
11	−0.013	(0.022)	−0.016	(0.021)	−0.014	(0.022)	72,010	0.219	0.273	0.219
12	−0.003	(0.021)	−0.006	(0.020)	−0.004	(0.021)	71,806	0.229	0.288	0.229
13	0.002	(0.020)	−0.002	(0.019)	0.001	(0.020)	71,603	0.238	0.302	0.238
14	−0.000	(0.018)	−0.003	(0.018)	−0.001	(0.019)	71,400	0.245	0.315	0.246
15	−0.006	(0.017)	−0.009	(0.017)	−0.007	(0.018)	71,193	0.252	0.327	0.252
16	−0.005	(0.017)	−0.008	(0.016)	−0.005	(0.017)	70,990	0.258	0.338	0.258
17	−0.009	(0.017)	−0.013	(0.016)	−0.010	(0.017)	70,788	0.263	0.349	0.263
18	−0.009	(0.016)	−0.012	(0.015)	−0.010	(0.016)	70,587	0.267	0.358	0.267
19	−0.013	(0.016)	−0.017	(0.015)	−0.014	(0.016)	70,387	0.270	0.367	0.270
20	−0.013	(0.015)	−0.017	(0.014)	−0.013	(0.015)	70,182	0.272	0.375	0.273
Fixed effects	None		Team		Season					

Note: Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent n games for teams whose coach quit their post, over and above teams who experience no coaching turnover. Models contain no balancing weights. Cluster robust standard errors in parentheses (clustered at the team level).

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A5 Multinomial logistic regression, determinants of dismissals and quits.

Variables	(1) Dismissal	(2) Quit
Team performance		
Surprise $t-1$	−0.312***	−0.123**
	(0.035)	(0.051)
Surprise $t-2$ to $t-5$	−0.155***	−0.130***
	(0.024)	(0.036)
Surprise $t-6$ to $t-10$	−0.024	−0.035
	(0.024)	(0.035)
Mean points prev 10 games	−0.957***	−0.271
	(0.189)	(0.264)
Position	−0.031***	−0.048***
	(0.011)	(0.019)
Position squared	0.001**	0.001***
	(0.000)	(0.000)
Last season position	0.002	−0.000
	(0.002)	(0.003)
Coach characteristics		
Tenure	−0.002**	0.006***
	(0.001)	(0.001)
Experience	−0.039***	−0.019
	(0.008)	(0.014)
Age	−0.007	−0.302***
	(0.057)	(0.087)
Age squared	0.000	0.003***
	(0.001)	(0.001)
N prev HC jobs	0.050***	0.041*
	(0.014)	(0.022)
Internal appointment	0.025	−0.428**
	(0.115)	(0.198)
Previous promotion	−0.265***	0.048
	(0.076)	(0.122)
Previous cup	−0.226**	0.275*
	(0.103)	(0.143)
Previous relegation	0.196**	−0.266**
	(0.079)	(0.134)
Ex player	−0.218**	−0.486***
	(0.109)	(0.181)
Season progress		
Proportion of games remaining	4.983***	−0.777
	(0.652)	(1.419)
Proportion of games remaining squared	−5.059***	0.373
	(0.638)	(1.425)
Last game of season	4.638***	5.270***
	(0.166)	(0.299)
Observations	66,157	66,157

Note: Standard errors in parentheses. Estimating the determinants of dismissals and quits using a multinomial logistic regression model. All the leagues and seasons included.

***$p<0.01$; **$p<0.05$; *$p<0.1$.

TABLE A6 Excluding relegations.

Mean points per game next … games	Dismissals (1) Coeff	SE	(2) Coeff	SE	(3) Coeff	SE	N	Quits (4) Coeff	SE	(5) Coeff	SE	(6) Coeff	SE	N
1	−0.027	(0.048)	−0.003	(0.045)	−0.033	(0.047)	59,933	0.042	(0.072)	−0.005	(0.068)	0.048	(0.072)	59,449
2	0.036	(0.035)	0.033	(0.033)	0.034	(0.035)	59,781	0.023	(0.054)	0.009	(0.050)	0.018	(0.053)	59,300
3	0.049*	(0.029)	0.039	(0.027)	0.048*	(0.029)	59,627	0.035	(0.046)	0.016	(0.042)	0.032	(0.047)	59,148
4	0.045*	(0.026)	0.034	(0.024)	0.043*	(0.025)	59,473	0.018	(0.041)	0.008	(0.036)	0.020	(0.041)	58,994
5	0.019	(0.023)	0.009	(0.021)	0.018	(0.023)	59,318	0.015	(0.037)	−0.005	(0.033)	0.019	(0.037)	58,840
6	0.009	(0.022)	−0.000	(0.020)	0.008	(0.021)	59,163	0.026	(0.034)	0.008	(0.030)	0.029	(0.034)	58,687
7	−0.005	(0.020)	−0.015	(0.018)	−0.006	(0.020)	59,009	0.023	(0.032)	0.002	(0.028)	0.024	(0.032)	58,535
8	−0.003	(0.019)	−0.014	(0.017)	−0.003	(0.019)	58,853	0.017	(0.030)	−0.003	(0.026)	0.017	(0.030)	58,380
9	−0.012	(0.019)	−0.026	(0.017)	−0.011	(0.019)	58,696	0.010	(0.029)	−0.013	(0.025)	0.010	(0.029)	58,227
10	0.002	(0.018)	−0.014	(0.016)	0.002	(0.018)	58,537	0.005	(0.028)	−0.020	(0.024)	0.005	(0.028)	58,073
11	0.001	(0.017)	−0.012	(0.015)	0.001	(0.017)	58,378	−0.007	(0.027)	−0.032	(0.023)	−0.005	(0.027)	57,915
12	−0.004	(0.017)	−0.016	(0.014)	−0.004	(0.016)	58,217	−0.000	(0.026)	−0.025	(0.022)	0.002	(0.026)	57,757
13	0.005	(0.016)	−0.007	(0.014)	0.005	(0.016)	58,057	0.007	(0.025)	−0.019	(0.021)	0.009	(0.025)	57,600
14	0.008	(0.016)	−0.003	(0.014)	0.008	(0.016)	57,896	0.007	(0.025)	−0.018	(0.021)	0.009	(0.025)	57,443
15	0.009	(0.016)	−0.002	(0.013)	0.010	(0.016)	57,735	−0.001	(0.024)	−0.021	(0.020)	0.001	(0.024)	57,282
16	0.012	(0.015)	0.001	(0.013)	0.013	(0.015)	57,572	−0.001	(0.024)	−0.022	(0.020)	−0.000	(0.023)	57,123
17	0.017	(0.015)	0.004	(0.013)	0.017	(0.015)	57,411	−0.006	(0.023)	−0.025	(0.019)	−0.006	(0.023)	56,964
18	0.015	(0.015)	0.001	(0.012)	0.015	(0.014)	57,250	−0.005	(0.023)	−0.017	(0.019)	−0.004	(0.022)	56,806
19	0.020	(0.014)	0.006	(0.012)	0.020	(0.014)	57,087	−0.008	(0.022)	−0.020	(0.019)	−0.007	(0.022)	56,649
20	0.019	(0.014)	0.004	(0.012)	0.020	(0.014)	56,925	−0.007	(0.022)	−0.020	(0.018)	−0.005	(0.022)	56,488
Fixed effects	None		Team		Season			None		Team		Season		

Note: These models exclude the first year after a team is relegated to a lower division. Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent n games for teams who dismissed or their coach, or the coach quit their post, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).

***$p<0.01$; **$p<0.05$; *$p<0.1$.

TABLE A7 Excluding promotions.

	Dismissals							Quits						
	(1)		(2)		(3)			(4)		(5)		(6)		
Mean points per game next ... games	*Coeff*	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*N*	*Coeff*	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*N*
1	0.009	(0.047)	0.037	(0.045)	−0.000	(0.046)	59,919	0.015	(0.072)	−0.051	(0.068)	0.014	(0.072)	59,415
2	0.049	(0.034)	0.046	(0.032)	0.046	(0.034)	59,766	0.014	(0.054)	−0.004	(0.051)	0.011	(0.053)	59,265
3	0.070**	(0.028)	0.059**	(0.027)	0.068**	(0.028)	59,611	0.036	(0.047)	0.014	(0.042)	0.034	(0.047)	59,112
4	0.062**	(0.025)	0.052**	(0.024)	0.060**	(0.025)	59,456	0.008	(0.041)	−0.002	(0.036)	0.010	(0.041)	58,958
5	0.039*	(0.022)	0.027	(0.021)	0.038*	(0.022)	59,300	0.009	(0.037)	−0.016	(0.033)	0.011	(0.037)	58,803
6	0.025	(0.021)	0.012	(0.020)	0.023	(0.021)	59,144	0.025	(0.035)	0.005	(0.030)	0.026	(0.034)	58,649
7	0.009	(0.020)	−0.005	(0.018)	0.008	(0.020)	58,988	0.026	(0.033)	0.001	(0.028)	0.026	(0.032)	58,496
8	0.009	(0.019)	−0.005	(0.017)	0.009	(0.019)	58,829	0.021	(0.031)	−0.006	(0.026)	0.020	(0.030)	58,339
9	0.003	(0.019)	−0.015	(0.017)	0.003	(0.018)	58,669	0.017	(0.029)	−0.016	(0.024)	0.018	(0.029)	58,182
10	0.015	(0.018)	−0.003	(0.016)	0.015	(0.017)	58,507	0.012	(0.028)	−0.023	(0.023)	0.013	(0.028)	58,025
11	0.011	(0.017)	−0.003	(0.015)	0.011	(0.017)	58,345	0.000	(0.027)	−0.036	(0.023)	0.001	(0.027)	57,864
12	0.003	(0.016)	−0.012	(0.014)	0.004	(0.016)	58,182	0.008	(0.027)	−0.024	(0.022)	0.011	(0.027)	57,704
13	0.007	(0.016)	−0.007	(0.014)	0.007	(0.016)	58,020	0.012	(0.026)	−0.021	(0.021)	0.014	(0.026)	57,545
14	0.011	(0.016)	−0.004	(0.014)	0.011	(0.016)	57,858	0.015	(0.025)	−0.019	(0.021)	0.016	(0.025)	57,386
15	0.012	(0.015)	−0.002	(0.013)	0.012	(0.015)	57,695	0.008	(0.025)	−0.019	(0.020)	0.009	(0.025)	57,223
16	0.012	(0.015)	−0.003	(0.013)	0.012	(0.015)	57,530	0.010	(0.024)	−0.017	(0.020)	0.011	(0.024)	57,062
17	0.015	(0.015)	0.001	(0.013)	0.015	(0.014)	57,367	0.006	(0.024)	−0.020	(0.019)	0.006	(0.023)	56,902
18	0.015	(0.014)	−0.001	(0.012)	0.015	(0.014)	57,204	0.009	(0.023)	−0.013	(0.019)	0.009	(0.023)	56,742
19	0.021	(0.014)	0.004	(0.012)	0.021	(0.014)	57,039	0.005	(0.023)	−0.017	(0.019)	0.007	(0.023)	56,583
20	0.022	(0.014)	0.004	(0.012)	0.022*	(0.013)	56,875	0.008	(0.023)	−0.016	(0.019)	0.010	(0.023)	56,420
Fixed effects	None		Team		Season			None		Team		Season		

Note: These models exclude the first year after a team is promoted to a higher division. Each coefficient is the result of a separate model. Coefficients report the additional points per game over the subsequent n games for teams who dismissed or their coach, or the coach quit their post, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A8 Modelling outcomes using a poisson regression.

	Dismissals							Quits						
	(1)		(2)		(3)			(4)		(5)		(6)		
Mean points per game next … games	*Coeff*	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*N*	*Coeff*	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*N*
1	−0.004	(0.033)	0.020	(0.035)	−0.009	(0.033)	65,603	0.014	(0.049)	−0.015	(0.055)	0.014	(0.049)	65,048
2	0.025	(0.025)	0.024	(0.027)	0.023	(0.025)	65,440	−0.001	(0.037)	−0.006	(0.040)	−0.007	(0.037)	64,888
3	0.037*	(0.021)	0.031	(0.023)	0.036*	(0.021)	65,275	0.017	(0.035)	0.008	(0.037)	0.013	(0.035)	64,725
4	0.029	(0.019)	0.022	(0.020)	0.028	(0.019)	65,110	0.002	(0.031)	−0.000	(0.031)	0.002	(0.031)	64,561
5	0.012	(0.017)	0.004	(0.017)	0.012	(0.016)	64,944	0.002	(0.028)	−0.006	(0.029)	0.003	(0.028)	64,396
6	0.003	(0.016)	−0.005	(0.016)	0.003	(0.016)	64,778	0.011	(0.026)	0.003	(0.026)	0.011	(0.026)	64,232
7	−0.005	(0.015)	−0.016	(0.015)	−0.006	(0.015)	64,612	0.012	(0.024)	0.003	(0.024)	0.011	(0.024)	64,069
8	−0.004	(0.014)	−0.015	(0.014)	−0.004	(0.014)	64,443	0.008	(0.023)	−0.002	(0.023)	0.007	(0.023)	63,902
9	−0.011	(0.014)	−0.023*	(0.014)	−0.010	(0.014)	64,273	0.003	(0.022)	−0.009	(0.022)	0.003	(0.022)	63,736
10	−0.001	(0.013)	−0.014	(0.012)	−0.000	(0.013)	64,101	−0.001	(0.021)	−0.016	(0.021)	−0.001	(0.021)	63,569
11	−0.001	(0.012)	−0.012	(0.011)	−0.000	(0.012)	63,929	−0.008	(0.020)	−0.024	(0.020)	−0.008	(0.020)	63,398
12	−0.004	(0.012)	−0.016	(0.011)	−0.004	(0.012)	63,755	−0.004	(0.019)	−0.019	(0.019)	−0.003	(0.019)	63,228
13	0.001	(0.012)	−0.010	(0.010)	0.001	(0.011)	63,582	0.002	(0.019)	−0.015	(0.018)	0.003	(0.019)	63,058
14	0.004	(0.011)	−0.007	(0.010)	0.004	(0.011)	63,409	0.002	(0.018)	−0.015	(0.017)	0.002	(0.018)	62,888
15	0.004	(0.011)	−0.007	(0.010)	0.004	(0.011)	63,235	−0.004	(0.018)	−0.017	(0.017)	−0.003	(0.018)	62,714
16	0.005	(0.011)	−0.007	(0.010)	0.005	(0.011)	63,059	−0.003	(0.017)	−0.017	(0.016)	−0.003	(0.017)	62,542
17	0.008	(0.011)	−0.003	(0.009)	0.008	(0.011)	62,885	−0.007	(0.017)	−0.020	(0.016)	−0.007	(0.017)	62,371
18	0.008	(0.011)	−0.005	(0.009)	0.008	(0.010)	62,711	−0.006	(0.016)	−0.014	(0.015)	−0.005	(0.016)	62,200
19	0.013	(0.011)	0.000	(0.009)	0.013	(0.010)	62,535	−0.008	(0.016)	−0.017	(0.015)	−0.008	(0.016)	62,030
20	0.012	(0.010)	−0.001	(0.008)	0.013	(0.010)	62,360	−0.007	(0.015)	−0.017	(0.015)	−0.006	(0.015)	61,856
Fixed effects	None		Team		Season			None		Team		Season		

Note: Each coefficient is the result of a separate Poisson regression, estimating the additional points per game over the subsequent n games for teams who dismissed their coach, or the coach quit their post, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).

$^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$.

TABLE A9 Points share, GLM regressions.

	Dismissals							Quits						
	(1)		(2)		(3)			(4)		(5)		(6)		
Points share next ... games	*Coeff*	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*N*	*Coeff*	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*N*
1	−0.003	(0.014)	0.004	(0.015)	−0.005	(0.014)	65,603	0.007	(0.022)	−0.010	(0.024)	0.007	(0.022)	65,048
2	0.011	(0.011)	0.009	(0.012)	0.010	(0.011)	65,440	−0.001	(0.017)	−0.003	(0.018)	−0.002	(0.017)	64,888
3	0.016*	(0.009)	0.013	(0.010)	0.016*	(0.009)	65,275	0.008	(0.016)	0.004	(0.017)	0.006	(0.016)	64,725
4	0.013	(0.008)	0.009	(0.009)	0.012	(0.008)	65,110	0.001	(0.014)	0.000	(0.014)	0.001	(0.014)	64,561
5	0.005	(0.007)	0.002	(0.008)	0.005	(0.007)	64,944	0.001	(0.013)	−0.003	(0.013)	0.002	(0.013)	64,396
6	0.001	(0.007)	−0.002	(0.007)	0.001	(0.007)	64,778	0.005	(0.012)	0.002	(0.012)	0.005	(0.012)	64,232
7	−0.002	(0.006)	−0.007	(0.006)	−0.003	(0.006)	64,612	0.006	(0.011)	0.001	(0.011)	0.006	(0.011)	64,069
8	−0.002	(0.006)	−0.006	(0.006)	−0.002	(0.006)	64,443	0.004	(0.010)	−0.001	(0.010)	0.004	(0.011)	63,902
9	−0.005	(0.006)	−0.010*	(0.006)	−0.005	(0.006)	64,273	0.002	(0.010)	−0.004	(0.010)	0.002	(0.010)	63,736
10	−0.001	(0.006)	−0.006	(0.005)	−0.000	(0.006)	64,101	0.000	(0.010)	−0.007	(0.009)	0.000	(0.010)	63,569
11	−0.001	(0.005)	−0.005	(0.005)	−0.000	(0.005)	63,929	−0.003	(0.009)	−0.011	(0.009)	−0.003	(0.009)	63,398
12	−0.002	(0.005)	−0.007	(0.005)	−0.002	(0.005)	63,755	−0.001	(0.009)	−0.008	(0.008)	−0.000	(0.009)	63,228
13	0.000	(0.005)	−0.004	(0.004)	0.000	(0.005)	63,582	0.001	(0.009)	−0.006	(0.008)	0.002	(0.009)	63,058
14	0.002	(0.005)	−0.003	(0.004)	0.002	(0.005)	63,409	0.002	(0.008)	−0.006	(0.008)	0.002	(0.008)	62,888
15	0.002	(0.005)	−0.003	(0.004)	0.002	(0.005)	63,235	−0.001	(0.008)	−0.007	(0.008)	−0.001	(0.008)	62,714
16	0.002	(0.005)	−0.003	(0.004)	0.002	(0.005)	63,059	−0.001	(0.008)	−0.007	(0.008)	−0.001	(0.008)	62,542
17	0.004	(0.005)	−0.001	(0.004)	0.004	(0.005)	62,885	−0.003	(0.008)	−0.008	(0.007)	−0.003	(0.008)	62,371
18	0.004	(0.005)	−0.002	(0.004)	0.004	(0.005)	62,711	−0.002	(0.007)	−0.006	(0.007)	−0.002	(0.007)	62,200
19	0.006	(0.005)	0.000	(0.004)	0.006	(0.005)	62,535	−0.003	(0.007)	−0.007	(0.007)	−0.003	(0.007)	62,030
20	0.005	(0.005)	−0.001	(0.004)	0.006	(0.005)	62,360	−0.003	(0.007)	−0.007	(0.007)	−0.002	(0.007)	61,856
Fixed effects	None		Team		Season			None		Team		Season		

Note: The outcome 'Points Share Next ... Games' is defined as Total Points Over Next ... Games/Maximum Attainable Points over that period. Each coefficient is the result of a separate model, reporting the additional points share over the subsequent n games for teams who dismissed or their coach, or the coach quit their post, over and above teams who experience no coaching turnover. Cluster robust standard errors in parentheses (clustered at the team level).

***$p<0.01$; **$p<0.05$; *$p<0.1$.