



Time To Go? Head Coach Quits and Dismissals in Professional Football

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Accepted: 20 October 2020 / Published online: 5 November 2020
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Abstract

That football Head Coaches will be dismissed for poor performance and will quit when they have better outside options seems obvious. But owners may find it hard to distinguish poor performance from bad luck and may find it difficult to identify and attract talented Head Coaches from other clubs even if their current Head Coach is performing below expectations. Equally, Head Coaches may have few options to move to better clubs even when they are performing well. Using rich data on Head Coach characteristics we identify determinants of quits and dismissals across four professional football leagues over the period 2002–2015. We find that Head Coaches' probabilities of dismissal are significantly lower when the team is performing above expectations, with the effect strongest for recent games. However, in contrast to earlier studies, we find that performing above expectations also reduces the probability of Head Coach quits. Head Coach success in the past, as well as Head Coach experience, reduce the probability of being dismissed, even when conditioning on team performance, suggesting Head Coach human capital has some 'protective' effect in managerial careers. Past experience has little effect on quit probabilities—with the exception of tenure at the current employer, which is associated with lower quit rates. We test the robustness of our results by confining estimates to first exits, within-season departures and by dealing with unobserved Head Coach heterogeneity.

Keywords Quits · Dismissals · Managerial performance · Team performance · Football · Competing risks

JEL Classifications J23 · J24 · J63 · J64

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1 Introduction

In modern businesses, owners rely on managers to run their firms with a view to maximising profits. If the firm is a listed company, owners will observe performance annually and, in the light of company performance and ambient labour market conditions, choose how to reward or punish senior management. In the absence of real time performance data and given the costliness of monitoring the activities of senior executives (Bandiera et al. 2020) owners may use proxy measures of corporate performance, such as share price movements, to up-date their information regarding how well senior management are performing. Share price movements and annual profitability may reflect many factors, including changes in market sentiment and changes in business conditions, some beyond the control of the senior executives. Furthermore, even though Chief Executive Officers (CEOs) have an important role in determining the productivity of all other employees due to their position at the apex of the organization (Rosen 1990), it is extremely difficult to identify the causal impact of leaders on organizational performance.¹ Nevertheless, CEOs are formally responsible for the corporation's performance and may therefore expect that performance to be reflected in their compensation packages and the longevity of any employment contract they may be offered.

When a firm is performing poorly, or more poorly than expected, the CEO can expect to be under pressure to “turn things around” and, if this does not happen, he/she may be under threat of dismissal. Poor performance of the firm may be directly related to the decisions or indecision of top executives, or may simply be “bad luck”, as in the case of deteriorating market conditions.² Conversely, if a firm is performing very well, other firms may treat this as a signal of the CEO's high ability and seek to poach the CEO. At the very least, the CEO may use good performance in on-the-job search to secure a better job offer from another firm.

In this paper, we identify the factors that determine senior executive turnover in a single, global industry where owners receive weekly updates on firm performance. We do so by modelling senior executives' time to exit from a firm, distinguishing between firms' decisions to dismiss an employee and quits, which are employee decisions to leave. The industry consists of small to medium sized businesses offering a single service competing directly against one another in a transparent fashion. Market conditions are very stable over the period of a few years and there are few exogenous factors in this market that can heavily influence firm performance in the short run. So it is, perhaps, unsurprising to find that firm success or failure is often attributed to the CEO.

The industry is professional football and the firms are football clubs.³ The “CEO” role is performed by Head Coaches—sometimes referred to as “managers”—who

¹ Efforts at doing so rely on exogenous changes in personnel associated with death or hospitalization. Examples include Besley et al. (2011) on heads of government and Bennesen et al. (2012) on CEOs.

² For this reason, owners often use the firm's performance relative to its competitors to determine executive compensation, thus conditioning on the market conditions all firms in the industry face (Bertrand and Mullainathan 2001).

³ In the United States these would be termed “soccer” teams because the term “football” is reserved for American Football.

are appointed to run team affairs. Although the scope of the role varies across countries and even within country depending on club owners' preferences, most Head Coaches have the power to recruit football players to the squad, and Head Coaches pick the team for games from that squad.⁴ Head Coaches are also responsible for recruiting back room support staff and for coaching the tactics used to beat opponents. It seems reasonable to assume, therefore, that Head Coaches play a crucial role in determining team performance, even though this causal impact has proven rather difficult to identify in practice.⁵

Club owners are able to update their information on Head Coach performance with the results from each game, which tend to happen at least 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, something that is harder to do in circumstances where owners only receive annual financial accounts and find monitoring executive performance costly.

Whereas football players can only be traded at particular times during the football season, Head Coaches can be laid off or hired throughout the season, as well as in the closed season between May and August. Head Coaches are also able to signal how good they are to prospective employers on a weekly basis through their team's performance, which is often attributed to the Head Coach. Prospective employers are therefore able to update their assessments of Head Coach quality weekly, and may well seek to poach rival teams' Head Coaches, creating strong incentives for Head Coaches who are performing well to quit their existing employer in favour of another, subject to negotiation over early departure clauses in their contracts of employment.

Using a particularly large and rich data set on Head Coaches from the first two tiers of four European leagues over the period 2002–2015, we estimate competing risks models for quits and dismissals. We find Head Coaches' probabilities of dismissal are significantly lower when the team is performing above expectations, with the effect strongest for more recent games. However, in contrast to earlier studies, we find that performing above expectations also reduces the probability of Head Coach quits. Head Coach success in the past, as well as Head Coach experience, reduce the probability of being dismissed, even when conditioning on team performance, suggesting that Head Coach human capital has some 'protective' effect in managerial careers. Past experience has little effect on quit probabilities—with the exception of tenure at the current employer, which is associated with lower quit rates. We test the robustness of our results by confining estimates to first exits, within-season departures and by modelling unobserved Head Coach heterogeneity.

⁴ In Continental Europe hiring and release of players is handled by the Director of Football with input from the Head Coach.

⁵ Van Ours and Van Tuijl (2016) is an important recent contribution to this literature. They find improvements in team performance after coach dismissal are accounted for by regression to the mean, a finding which is consistent with much of the literature they review.

2 Theory and Empirical Evidence

In the standard model of employment relationships, workers are hired when the match-specific surplus generated for the firm exceeds the costs of hire. Termination of the contract will occur through dismissal by the employer, or a quit by the worker, where the value of that match for one or both parties falls below the value of an outside option (Farber 1999). Worker actions such as gross negligence, incompetence or misconduct substantially reduce the net value of the contract to the employer thus resulting in dismissal. Over the life cycle, a gradual deterioration in worker performance, for example through the degradation of skills or age-related health issues, will reduce the match-specific surplus, especially if the experienced incumbent has benefited from an upward sloping wage profile.⁶

Monitoring costs are often too high to establish with any certainty how the productivity of employees varies over time. Exceptions include circumstances in which output is readily identifiable as individual effort, as in the case of academics' publications (Levin and Stephan 1991). In the case of CEOs, organizational performance is often attributed to them, whether this is justified or not. The costliness of monitoring their inputs means owners prefer to link their compensation to performance outcomes, thus allowing for continual adjustment in the rules governing the sharing of surplus between the owner and manager (the principal and the agent). Performance pay is akin to wage renegotiation in being able to limit inefficient worker-firm separations (Gielen and van Ours 2006). Even then the firm must appraise the value of the worker-firm match relative to the value of hiring a new worker.

Although, in theory, the threat of dismissal may be used by owners to discipline managers, the empirical literature indicates that, until recently, CEOs were rarely explicitly fired for poor performance, leading Jensen and Murphy (1990) to conclude that the dismissal threat was not an important factor in incentivising CEOs. This view is supported by Murphy's (1999: 2542 ff) review of the empirical literature. However, a contrary view has been offered by Jenter and Lewellen (2019) who argue, based on analyses of listed firms in the United States over the period 1993–2011, that between two-fifths and one-half of CEO turnovers would not have happened had performance been 'good' (what they term "performance-induced turnover").

Firms face the problem that CEOs are heterogeneous in ability and it is hard to identify which are the more talented among them. There is ample evidence that CEOs are heterogeneous in quality and that this affects firm policies (Bertrand and Schoar 2003). Furthermore, leaders affect team productivity (Lazear et al. 2015). Muehlheusser et al. (2016) present evidence of substantial heterogeneity in Head Coach ability in the German *Bundesliga*, where team performance varies according

⁶ Contracts may also cease when workers retire. Under Lazear's (1979) compulsory retirement model firms pay young workers below their marginal product during training, setting the wage profile such that investments in firm-specific human capital are rewarded in the long-run. Workers are incentivised by retirement packages which are triggered around the time the worker's marginal product is exceeded by his marginal labour costs.

to the ability of the incoming Coach. Theory suggests inefficient hiring in talent markets whereby mediocre workers are re-hired in the face of risk associated with appraising the talent of workers that are new to an industry (Tervio 2009). This market failure arises where talent is industry-specific, is only revealed on the job and, once revealed, becomes public information. More productive firms hire those revealed to be high ability whereas less productive firms must either experiment with untested new workers or hire managers who have records of failure in other firms. Where there is insufficient discovery of new talent, risk-averse firms tend to re-hire some workers known to be mediocre. Peeters et al. (2017) confirm that this market failure exists among Head Coaches in professional football in England.

We contribute to the literature on managerial turnover in two ways. First, our large sample and sizeable number of quits, as well as dismissals, gives us the power to detect influences on these outcomes that may not have been possible in previous studies with smaller samples in single country settings. Second, our data contain a richer set of Head Coach characteristics than is commonly available. In combination with week-by-week team performance relative to expectations, as captured from betting market data, these rich data offer greater insight into the factors affecting coach exits than has been possible until now.

The theory and evidence presented above in relation to CEOs have implications for Head Coach quits and dismissals in professional football. We use these insights to test two hypotheses with our data.

Hypothesis 1 Good performance and performance above expectations reduces the likelihood of dismissal and increases the likelihood of quitting.

Team owners are able to update their information on Head Coach talent on a weekly basis, comparing the performance of their Head Coach to others. Team performance should have strong predictive power in establishing whether a Head Coach will be dismissed. This proves to be the case in the nine studies on within-season coach dismissals reviewed by Van Ours and Van Tuijl (2016: 593) covering leagues in England, Germany and Spain. Pieper et al. (2014) confirm the importance of team performance for Head Coach dismissal in the German Bundesliga. But they also introduce expectations using betting odds and find that these also play an important role in determining the probability of Head Coach dismissals. Using data from the Dutch league, Van Ours and Van Tuijl (2016) also confirm the importance of expectations in determining the probability of Head Coach dismissals. They also extend the literature in two ways. First, they supplement within-season estimates with coach spell estimates where coach spells span seasons, so that they can incorporate dismissals in the closed season. Results are similar. Second, they are able to identify quits. However, they find no significant effects of expected team performance on quits, perhaps because these are rare events in their data.

In keeping with this literature, we suspect that good performance, and performance above expectations, will lower dismissal rates by increasing the net value of the contract to the employer. However, they may also increase the likelihood of a quit due to “poaching” behaviour on the part of competing teams which increases

the job offer rate for Head Coaches. Conversely, a sequence of bad results may be perceived as an indicator of poor Head Coach performance, rather than simply a bad run of luck [what Rabin and Vayanos (2010) refer to as a “hot-hand fallacy”], thus raising the likelihood of dismissal and reducing the opportunity to quit for another job.

Hypothesis 2 Head Coach experience will be valued by employers, reducing the likelihood of Head Coach dismissal. However, effects of Head Coach experience on quits are theoretically ambiguous a priori.

The literature finds that the personal attributes of Head Coaches are relatively unimportant in explaining dismissals and quits. Van Ours and Van Tuijl (2016) say this is why they remove them from their preferred model specification (p. 598 and footnote 8). The exception is coach age which appears to be positively related with dismissal probabilities in their study and others that they review. In our analysis, we make a distinction between overall coaching experience and tenure at current club as alternative measures of experience.

We anticipate that aspects of human capital, such as coach experience, will be valued by employers. Experience potentially protects the Head Coach from dismissal even when performance is below expectations. However, this is not what Van Ours and Van Tuijl (2016) find in their study. Familiarity with the club, as indicated by time spent at the club as a coach or player, should lower dismissal probabilities by providing workers with insights about the specifics of the club and its workings which can then raise labour productivity (Becker 1962). Signals of success in the coach’s previous jobs (such as winning cups or titles, or getting clubs promoted) will also delay the point at which the employer dismisses a coach conditional on performance.

In contrast, the effects of Head Coach experience on quits are indeterminate, a priori. On the one hand, the likely market value of past coaching experience and past coach performance in tackling management problems in a new environment may raise job offer arrival rates, potentially increasing quits. On the other hand, greater experience at one’s current employer, as well as prior experience at the club (either as a coach or player), can indicate a high-quality job match relative to outside options, reducing the Head Coach’s likelihood of accepting outside offers (Stevens 2003). The threat of outside offers will likely trigger counter-offers from the current employer.

3 Data and Empirical Approach

3.1 Data

We have data for 642 Head Coaches who were in charge of football league games played by the 206 teams in the top two tiers of professional football in Germany, France, Spain and Italy covering the seasons 2002–2003 to 2014–2015. This period

Table 1 Proportion of coaches who experience n exits, split by type of exit

Proportion of coaches with n events	All exits %	Cum.%	Dismissals %	Cum.%	Quits %	Cum.%
0	4.52	4.52	15.42	15.42	60.12	60.12
1	42.21	46.73	48.29	63.71	22.27	82.40
2	22.74	69.47	17.45	81.15	12.31	94.70
3	11.84	81.31	8.72	89.88	4.21	98.91
4	6.39	87.69	5.76	95.64	0.62	99.53
≥ 5	12.31	100.00	4.37	100.00	0.47	100.00

covers 71,176 games, though after dropping observations with missing data, and games where an interim manager was in charge, our final sample is based on 64,495 games covering 1407 unique coaching spells. The data are a flow sample in that we observe the start date for all coaches' initial employment spells, including those that overlap the start of the initial football season in our data. Each spell ends with the Head Coach leaving due to dismissal by the club or a voluntary quit, or else the Coach remains in post.

Our recording of dismissals and quits is taken from Wikipedia Head Coach biographies that are cross-checked against local media sources. In some cases, a Head Coach is stated as having departed by 'mutual consent'. In reality, these are circumstances in which the Head Coach has been asked to leave, but the club agrees to classify the departure as a joint decision to allow the Head Coach to "save face". We have classified these cases as dismissals.

A coach spell is defined as the number of days since the Head Coach started the job. The closed season is included in the number of days. Of the 1407 coaching spells in our sample, 944 ended in dismissal and 358 ended in a Coach quitting. In the remainder (105 spells) the Head Coach remained in post. The average coaching spell lasted for 453 days (s.d. = 488 days, minimum = 16 days, maximum = 5802 days) before an exit. The mean number of days that elapse prior to a dismissal is 380 days (s.d. = 381, min = 16, max = 3797), compared to 645 days before a quit (s.d. = 660, min = 33, max = 5802).

Nearly all coaches in the sample contribute at least one exit from a club over the sample period, the median being two exits (Table 1). One in six coaches experienced four or more exits, while the maximum number of job spells held during the sample was nine. Dismissals are far more common than quits; whereas two-fifths of Coaches had never quit, only 15% of Coaches had never been dismissed.

A large number of coaching exits occur during the closed season, which in the major European football leagues runs from early May until early August. Players take a break before pre-season training commences, where this break also coincides with the start of the summer transfer window. For clubs wishing to make a coaching change, this is the most sensible time for this to happen, since a new coach will have the most time to implement their own training methods and assemble a new squad. For coaches wishing to leave the club, the closed season is when their contracts will

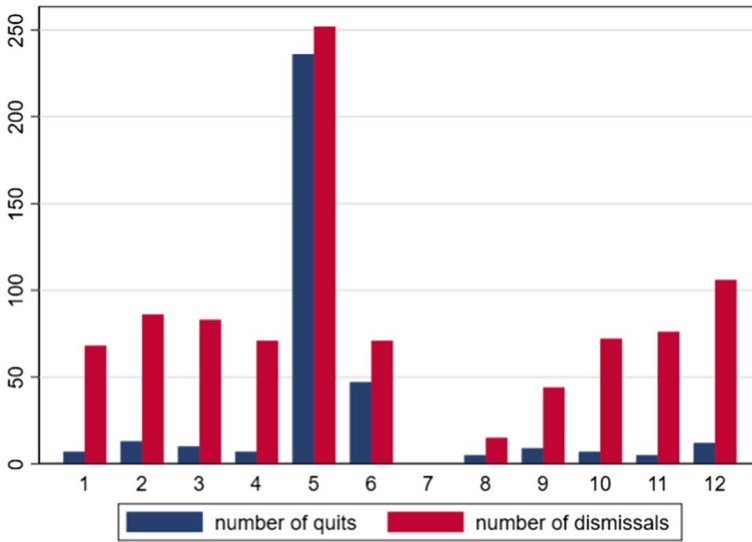


Fig. 1 Number of quits/dismissals by month

expire so some departures may just reflect the non-renewal of fixed term contracts. About 42% of all exits occur during the closed season, with almost one-third (31%) of dismissals, and almost three-quarters (74%) of quits occurring in the closed season.

Graphically, we can see the number of quits and dismissals per month in Fig. 1. We observe a large spike in both quits and dismissals in May, the final month of the season. Of these exits in May, over 90% occur in the days immediately following the conclusion of the season. We account for this particular feature of coaching exits in our model specifications, by estimating models both for all exits, and confined to within season exits only. In our across-season estimates, we include an indicator variable identifying if the exit occurred during the closed season.

3.2 Estimation

We apply survival analysis techniques to examine Head Coach exits. Introducing some terminology, there are two functions defined by survival analysis; the survivor function and the hazard function. A survivor function defines the probability of survival beyond time t , with failure observed at time T .

$$S(t) = \text{Prob}(T > t) = 1 - F(t)$$

The survivor function is the complement of the cumulative distribution function $F(t)$ and is a non-increasing function equal to one at time $t=0$ (when all subjects are at risk) and will tend towards zero as time approaches infinity.

The hazard function defines the instantaneous risk of failure at time t given that failure has not yet occurred.

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\text{Prob}(t < T \leq T + \Delta t | T > t)}{\Delta t}$$

Given that our data capture multiple types of failure (quits and dismissals), conventional methods such as the Cox Proportional Hazards (Cox 1972) model are unsuitable because the observation of another, competing event impedes observing the failure event of interest. Instead, we apply a competing risks analysis which is suitable when subjects are exposed to more than one type of failure (Gutierrez 2010). Competing events are different from censored observations which prevent observation of an event; a competing event prevents the event from occurring altogether. In our setting Head Coach Quits and Dismissals can be thought of as competing risks, since only one of the events can occur first, and after occurring means we cannot observe the other (competing) event.

Under competing risks, the interpretation of an (all-cause) survivor function is problematic, since it is unlikely that competing events are independent. So instead, for a categorical event variable R , where $R=0$ if a subject is censored and $R=m$ if a subject failed through cause $m=1, \dots, M$ consider a Cumulative Incidence Function (CIF), defined as the probability that a subject will experience failure type m by time t .

$$F_m(t) = \text{Prob}(T \leq t, R = m)$$

Our preferred specifications rely on competing risks regressions, using the method of Fine and Gray (1999). To model the effect of a covariate on the CIF, define a variable T^* as follows

$$T^* = \begin{cases} T, & R = m \\ \infty, & R \neq m \end{cases}$$

The hazard function associated with T^* (known as the sub-distribution hazard) is:

$$\gamma_m(t) = \lim_{\Delta t \rightarrow 0} \frac{\text{Prob}(t < T \leq T + \Delta t, R = m | T > t \cup (T < t \cap R \neq m))}{\Delta t}$$

A sub-distribution hazard removes a subject from the risk set only when the event of interest occurs, as opposed to when any event occurs for a cause-specific hazard. The Fine–Gray model assumes proportional hazards on the sub-distribution hazard such that

$$\gamma_m(t; \mathbf{x}) = \gamma_{m0}(t) \exp(\mathbf{x}' \boldsymbol{\beta})$$

Fine and Gray (1999) specify that the vector of covariates (labelled \mathbf{x} in the above equation) are time-independent i.e. do not change over the time at risk. However, the official Stata command to implement the regression does allow for the variables to be specified as time varying, and it is not uncommon to see time-varying covariates appear in such estimates. Austin et al. (2020) advise caution against including time varying covariates in such regressions, due to difficulty in estimating their effects on the CIF (similar interpretability issues also arise when applying Cox regressions

with no competing risks). Certain time varying regressors are permissible however.⁷ Since our data are at the game level variables are not actually time varying at this granular unit of observation, though if they were aggregated over an entire coaching spell, they would be time varying.

One final point to consider on estimation is the role of unobserved heterogeneity. In survival analysis, subjects could fail due to some (real or hypothetical) unobserved variable(s), referred to as frailty. Frailty models are convenient in the analysis of clustered survival data, where sub-groups of the population may have correlated survival times. These ‘shared’ frailties are modelled by including a random variable z_j . For subject $i = 1, \dots, k$ in cluster $j = 1, \dots, J$, a subject will have a survival time T_{ij} with hazard

$$h(t; z_j, \mathbf{x}_{ij}) = z_j h_0(t) \exp(\mathbf{x}'_{ij} \boldsymbol{\beta})$$

such that all subjects in the same cluster follow the same frailty. Z is usually modelled with a gamma distribution, though any continuous function with positive support, mean one and finite variance suffices. This is straightforward to add to a parametric regression model or a Cox proportional hazards model for example, but unfortunately that is not true for competing risks models. Putter and van Houwelingen (2015) and references therein, show that competing risks models with frailties are unidentifiable apart from under stringent assumptions and can lead to models that violate the assumption of proportional hazards. As such, we will run robustness checks including frailty terms in a parametric regression framework. All competing risks models are run with robust standard errors clustered at the level of the Head Coach to prevent our inferences being plagued by frailty.

Our specifications take the following form.

$$\gamma_k(t; \mathbf{x}) = \gamma_{k0}(t) \exp \left(f(\text{Performance Variables, Team Experience Variables, General Experience Variables, Controls}) \right)$$

We include six performance variables to test hypothesis one. We include rank league position in the most recent game across the top two tiers and, following Stadtmann (2006) and Van Ours and Van Tuijl (2016), we incorporate a measure of ‘surprise’ regarding team performance. This captures the difference between the actual number of points obtained and the expected number of points based on bookmakers’ odds. These are average odds across five online bookmakers: William Hill, Ladbrokes, Stan James, Bet 365 and Gamebookers. The source is www.football-data.co.uk and betting odds are highly correlated across bookmakers. Using the betting odds and accounting for the bookmaker’s over-round, we compute each team’s probabilities for a win (pw), a draw (pd) and a loss (pl). These probabilities are each scaled by the sum of probabilities, $pw + pd + pl$, where this sum exceeds one to account for the bookmaker’s commission. Surprise is the actual points per

⁷ These are referred to as “external time-varying covariates”, which are those that may be involved in failure, but are not impacted upon by failure (i.e. there is no feedback the variable and the failure process).

match minus the expected number of points (where the expected number of points is $(pw \times 3) + pd$). The variable 'surprise' records this for the most recent match. A positive value on surprise indicates that performance has exceeded expectations. We also include cumulative lagged surprise which captures performance relative to expectations from two to five games ago and from six to ten games ago. Dummies indicating whether the team was promoted or relegated last season are also included but in some instances the current Head Coach would not have been in charge then.

To test our second hypothesis, we include variables capturing a Head Coach's previous experiences. We distinguish between two broad categories: experience with the current club and general experience (which includes past successes as a coach).⁸ For firm (i.e. club) specific experience, we include tenure at current team (defined as number of games managed) along with its square, dummies to indicate whether the coach is a former player at the club and whether the coach was an internal appointment, and the number of previous spells coaching the current club. This club specific experience can also be thought of as representing a "connection" between the coach, team and fans which may increase the value of staying at the club, lowering the quit probability as one might predict under Stevens' (2003) model.

Our measures of general experience include the total number of years of experience as a Head Coach (total years since first entering coaching) along with the squared value of experience. We also include the number of previous spells as a Head Coach and a dummy indicating whether the Coach is managing in their own country. For past successes, we include dummies indicating whether the Coach has ever been promoted, relegated or won a championship previously.

As controls, we include the position of the team at the end of the previous season (irrespective of who was coaching the team), plus a dummy identifying closed season departures, given the earlier discussion on this. We also include the number of games left until the end of the season, since an owner's decision may be swayed if they feel a Coach has time to improve early season results. We also include a set of country dummies and a set of season dummies, along with a dummy variable equal to one if the club is in the second division.

Table 2 below presents descriptive statistics of our variables. A correlation matrix can be found in the "[Appendix](#)".

4 Results

Below, we present results from the competing risks regressions for dismissals and quits, together with the associated Cumulative Incidence Functions (CIF). The CIFs show what the cumulative probability of being dismissed or quit is over time. We can see from Fig. 2 that the probability of dismissal rises sharply in the first

⁸ We also experimented with previous experience as a player in the spirit Goodall et al. (2011) who emphasise the value of experience playing a sport for success as a coach. We had data on whether the coach was an international player, whether they played in a top league and the number of years they played professionally, but these variables were insignificant in all models.

Table 2 Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
<i>Performance</i>					
League position	64,495	19.211	11.849	1	48
Surprise	64,495	0.012	1.198	-2.707	2.797
Cum. surprise games 2–5	64,495	0.062	2.373	-8.269	8.277
Cum. surprise games 6–10	64,495	0.077	2.649	-9.681	9.76
Promotion last season	64,495	0.054	0.225	0	1
Relegation last season	64,495	0.016	0.125	0	1
<i>Team experience</i>					
Tenure (n games)	64,495	48.297	51.252	1	456
Ex player	64,495	0.143	0.351	0	1
Internal appointment	64,495	0.127	0.333	0	1
Num. repeat spells	64,495	0.102	0.358	0	3
<i>General experience</i>					
Experience (years)	64,495	11.4	7.676	0	44
Num. prev jobs	64,495	4.36	3.894	0	23
Managing in own country	64,495	0.864	0.343	0	1
Previous promotion	64,495	0.532	0.499	0	1
Previous relegation	64,495	0.266	0.442	0	1
Previous championship	64,495	0.125	0.33	0	1
<i>Controls</i>					
Position end of last season	64,495	19.124	11.554	1	47
Games left	64,495	18.507	10.964	0	45
Closed season	64,495	0.01	0.097	0	1
Tier2	64,495	0.449	0.497	0	1

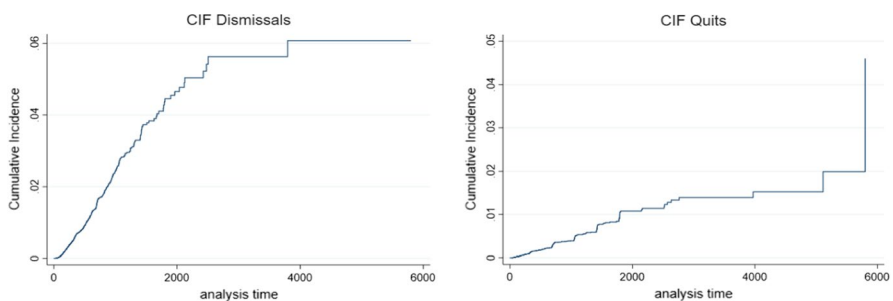
**Fig. 2** Cumulative incidence functions for dismissals and quits

Table 3 Competing risks models

Variables	All data, all events		Within season, all events	
	(1)	(2)	(3)	(4)
	Dismissal	Quit	Dismissal	Quit
<i>Performance</i>				
League position	1.167*** (0.011)	0.994 (0.013)	1.198*** (0.014)	1.130*** (0.025)
Surprise	0.600*** (0.026)	0.946 (0.046)	0.403*** (0.026)	0.774** (0.086)
Cum. surprise games 2–5	0.820*** (0.016)	0.958* (0.023)	0.747*** (0.015)	0.830*** (0.044)
Cum. surprise games 6–10	0.905*** (0.015)	0.970 (0.023)	0.865*** (0.015)	0.934 (0.047)
Promotion last season	0.986 (0.221)	0.712 (0.178)	0.973 (0.249)	0.486 (0.332)
Relegation last season	0.937 (0.361)	2.614** (1.124)	1.339 (0.590)	2.021 (1.535)
<i>Team experience</i>				
Tenure	0.961*** (0.002)	0.990*** (0.002)	0.943*** (0.003)	0.964*** (0.004)
Tenure squared	1.000075*** (0.000)	1.000 (0.000)	1.0001*** (0.000)	1.00007*** (0.000)
Ex player	0.821 (0.125)	0.769 (0.156)	0.700** (0.115)	0.761 (0.340)
Internal appointment	1.215 (0.183)	0.605** (0.130)	1.032 (0.179)	0.939 (0.404)
Num. repeat spells	0.972 (0.172)	1.481** (0.233)	1.136 (0.229)	1.247 (0.396)
<i>General experience</i>				
Experience	1.005 (0.024)	0.938*** (0.021)	0.996 (0.028)	0.952 (0.041)
Experience squared	0.999 (0.001)	1.002*** (0.001)	1.000 (0.001)	1.001 (0.001)
Num. prev jobs	1.060*** (0.023)	1.030 (0.025)	1.049* (0.029)	1.103** (0.051)
Managing in own country	0.828 (0.125)	0.952 (0.167)	0.761* (0.111)	0.801 (0.274)
Previous promotion	0.639*** (0.065)	1.112 (0.150)	0.526*** (0.063)	0.793 (0.191)
Previous relegation	1.348** (0.162)	0.740** (0.112)	1.339** (0.181)	0.831 (0.252)
Previous championship	0.728* (0.119)	0.969 (0.159)	0.416*** (0.091)	1.254 (0.416)

Table 3 (continued)

Variables	All data, all events		Within season, all events	
	(1)	(2)	(3)	(4)
	Dismissal	Quit	Dismissal	Quit
<i>Controls</i>				
Position end of last season	0.950*** (0.008)	0.999 (0.011)	0.950*** (0.010)	0.957** (0.021)
Games left	0.973*** (0.003)	0.980** (0.010)	0.965*** (0.004)	0.958*** (0.011)
Closed season	11.827*** (1.525)	112.834*** (25.310)		
Tier2	0.131*** (0.033)	0.751 (0.218)	0.056*** (0.017)	0.156*** (0.100)
Country dummies	Yes	Yes	Yes	Yes
Season dummies	Yes	Yes	Yes	Yes
Number of games	64,495	64,495	63,880	63,880

Standard errors clustered by coach shown in parenthesis

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Hazard rates are reported to 3 decimal places unless a significant hazard close to 1 required reporting more decimal places

2000 days (approx. 5 and a half years), flattening thereafter. The cumulative probability of quitting rises much more slowly and continues to rise after the 2000 mark.⁹

Table 3 presents estimates of the competing risks models. Time to exit is measured in days. The results displayed are sub-hazard ratios, not coefficients. Values greater than one indicate an increased risk, while values less than one indicate a reduced risk. For example, a value of 1.20 can be interpreted as a 20% increase in the sub-hazard ratio.

Models 1 and 2 present results for all events, including dismissals and quits that occur between seasons. When coaches leave after their contracts expire, typically at end of a season, it is difficult to make a clear separation between ‘dismissals’ and ‘quits’. To deal with this problem, Models 3 and 4 restrict analysis to within season events, resulting in a slightly lower sample size. We recognize that many head coach contracts expire when a given season ends and all coaches are face end-of-season performance reviews. At end of season, some coaches are released, without contract extension or renewal which we treat as a ‘fire’, while others leave voluntarily, most often to join other clubs but also to retire or pursue other activities, which we consider to be ‘quits’. The analysis on the subsample of within season exits gives an

⁹ Only 7 spells that end in a quit last longer than 2000 days. Ten spells that end in a quit last longer than 2000 days.

alternative approach to separation of dismissals and quits which is also in line with most literature on head coach turnover.

In keeping with *Hypothesis One*, improved performance and performance above expectations each reduce the likelihood of Head Coach dismissal, with the effect being slightly stronger for within season dismissals (Model 3). Owners place more weight on recent performance when triggering firings: the value on the hazard is closer to 1 for games 6–10 than games 2–5 and the most recent game. Irrespective of expectations, a larger number on league position (being lower down the table) is associated with a higher likelihood of dismissal.

Contrary to our priors, team performances above expectations reduce the probability of quitting where the effect is particularly strong in the within-season estimates (Model 4). One possible reason for this, discussed earlier, is that good performance triggers performance-related bonuses or renewal of Head Coaches' contracts on improved terms hence reducing the value of accepting outside offers. Running in the opposite direction is the fact that a lower league position increases the probability of a Coach quitting within season, with the effect similar in size to the increased probability of being dismissed. Some of these within-season quits may occur when Head Coaches see the "writing on the wall" and choose to quit before they are dismissed.

The models offer some support for the proposition in *Hypothesis Two* that Head Coach experience is valued by employers and protects them from dismissal even after conditioning on performance and performance expectations. Total experience as a Coach plays no significant role, but indicators of previous success (coaching a team that was promoted to a higher division or won a championship) reduce the likelihood of dismissal. Conversely, presiding over a previous relegation increases the probability of being dismissed from one's current job by around one-third. The number of previous jobs held might be valued by some owners looking for a Coach with a range of experiences—which could explain why it is positively linked to quit probabilities. But a larger number of previous jobs is also associated with higher within-season dismissal probabilities, perhaps indicating that there is a sub-set of Coaches that cycle from club to club despite poor success rates, in keeping with Peeters et al.'s (2017) study that alludes to a group of mobile 'mediocre managers'.

Experience at the club does appear to be valued by owners since, even conditioning on team success and expectations, the probability of being dismissed falls with tenure, albeit at a diminishing rate. The squared term implies that the log of the hazard ratio for dismissals is minimised at 265 games of tenure [from model (1)]. This value however, is well above the average tenure for coaches (mean = 48 games, std.dev = 51) so for most coaches this effect is approximately linear. Being an ex-player also lowers dismissal probabilities conditional on performance and expectations, although the coefficient is only significant within-season. The probability of quitting also falls with tenure at the club (again, an effect that diminishes with time), indicating a good job match for the Coach. Internal appointments also appear to be good job matches from the Coach's perspective since they reduce quit probabilities by about 40 per cent. The number of repeat spells at the club, on the other hand, is associated with higher quit probabilities, reminiscent of a 'revolving door' of highly mobile Head Coaches.

We do not observe Coaches' contracts directly but the model provides some insights into how they operate. As noted earlier, many contracts are subject to renewal at the end of the season so owners may be willing to wait until the end of the season before they make changes, especially if they are keen to limit financial and other liabilities which might result in "poaching" another team's manager, even if this appears optimal. Support for this "stickiness" hypothesis is indicated by the significant hazard on the dummy variable identifying the closed season in both the quits and dismissals models, suggesting that both teams and Head Coaches simply wait until the season ends before making changes.¹⁰ On the other hand, the likelihood of both quits and dismissals rises as the season end approaches, perhaps because teams seek to make changes at the "business end" of the season when the consequences of failure or success become increasingly apparent.¹¹

In Table 4 we present estimates confined to Head Coaches in their first jobs to see what happens when we remove repeat events which are dominated by Coaches who tend to move a lot. Discarding repeat events gives a smaller sample. Due to this smaller sample size, we had to drop season dummies from the Quit specifications. Models 5 and 6 consider all first events, while Models 7 and 8 consider only first events that fall within season. We drop the number of previous jobs and the number of previous spells as Head Coach at the same club from these specifications since these are all coaches in their first job, while we also drop Experience due to its collinearity with Tenure for first time Head Coaches.

Once again, as anticipated in *Hypothesis One*, performance above expectations is associated with a lower dismissal probability, with effects strongest for the most recent games. A lower (worse) league position is also associated with a higher probability of dismissal and, within season, of quits. General experience matters less for these first time coaches. If the Coach won promotion with the club, this is associated with a lower dismissal probability in the current season. A previous relegation experience no longer significantly affects dismissals. Even in these first jobs, tenure at the club matters as anticipated in *Hypothesis Two*; dismissal and quit probabilities fall with tenure, albeit at a diminishing rate, perhaps reflecting a good job match for the Coach and owners of the team. An internal appointment to a new first job is associated with a lower quit rate in Model 6, perhaps because a new Coach learning his trade is unlikely to attract early job offers from outside. The exit probabilities of ex-players are significantly lower. As before, Head Coach turnover is heavily concentrated in the closed season, though quits and dismissals are more likely later in the season.

¹⁰ Contracts often expire at a season's end, so some of these departures will reflect the non-renewal of fixed term contracts.

¹¹ Owners may be less concerned by early poor performance if they think there is sufficient time left in the season for a coach to "turn things round". Lower quit rates earlier on may also reflect the relative paucity of available job slots, thus limiting the job offer arrival rate.

Table 4 Competing risks models, time to first event

Variables	All data, first event		Within season, first events	
	(5)	(6)	(7)	(8)
	Dismissal	Quit	Dismissal	Quit
<i>Performance</i>				
League position	1.245*** (0.033)	1.029 (0.039)	1.285*** (0.045)	1.150*** (0.053)
Surprise	0.544*** (0.059)	0.931 (0.114)	0.323*** (0.054)	0.681* (0.141)
Cum. surprise games 2–5	0.872*** (0.038)	0.850*** (0.048)	0.792*** (0.044)	0.821* (0.088)
Cum. surprise games 6–10	0.909** (0.041)	0.958 (0.065)	0.841*** (0.044)	1.032 (0.126)
<i>Team experience</i>				
Tenure	0.941*** (0.007)	0.995 (0.006)	0.935*** (0.008)	0.972*** (0.009)
Tenure squared	1.0001*** (0.000)	1.000 (0.000)	1.0001*** (0.000)	1.00006*** (0.000)
Ex player	0.574** (0.144)	0.624 (0.287)	0.565** (0.164)	0.270* (0.213)
Internal appointment	0.903 (0.260)	0.463* (0.214)	0.728 (0.257)	0.802 (0.579)
<i>General experience</i>				
Managing in own country	0.440** (0.149)	3.498 (3.139)	0.600 (0.263)	1.497 (1.657)
Previous promotion (with team)	0.483** (0.146)	1.856 (0.804)	0.489* (0.186)	0.634 (0.451)
Previous relegation (with team)	1.705 (0.823)	0.807 (0.568)	2.294 (1.475)	2.997 (3.235)
Previous championship (with team)	1.045 (0.643)	0.618 (0.407)	1.586 (1.029)	0.069*** (0.070)
<i>Controls</i>				
Position end of last season	0.871*** (0.020)	0.980 (0.025)	0.891*** (0.028)	0.934* (0.035)
Games left	0.979** (0.009)	0.965 (0.028)	0.972*** (0.010)	0.949* (0.028)
Closed season	30.766*** (10.764)	43.564*** (26.103)		
Tier2	0.132*** (0.080)	0.737 (0.582)	0.032*** (0.027)	0.169 (0.238)
Country dummies	Yes	Yes	Yes	Yes
Season dummies	Yes	No	Yes	No
Observations	8,667	8,667	8,595	8,595

Standard errors clustered by coach shown in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 (continued)

Hazard rates are reported to 3 decimal places unless a significant hazard close to 1 required reporting more decimal places

5 Robustness Checks

In this section we run a robustness check introducing a shared frailty term to a Weibull regression to examine the role (if any) of unobserved Head Coach heterogeneity.¹² A Weibull regression is a parametric regression, where we assume a particular form for the baseline hazard. Weibull models are both a proportional hazards model and an Accelerated Failure Time (AFT) model (Jenkins, n.d.). In an AFT model, survival time is expressed as a linear model as follows

$$\log(t_i) = \mathbf{x}_i\boldsymbol{\beta} + z_i$$

where z is an error term. An AFT model simply scales time by a factor of $\exp(-\mathbf{x}_i\boldsymbol{\beta})$, such that failure time is either accelerated or decelerated.

For comparison purposes, we also run a Weibull regression with no frailty term. Models 9 and 11 report a Weibull regression with no frailty terms, while models 10 and 12 include a shared frailty term. As in previous tables, results are reported as hazard ratios.

A positive and significant value on p indicates that the hazard rises over time. The significant theta values confirm the presence of unobserved heterogeneity, possibly causing some Coaches to fail quicker than others. However, results are near identical with or without controlling for frailty and are generally consistent with the results found for the competing risks models. There are a small number of exceptions where results with frailty differ to those without. In the dismissal models, the number of repeat spells at the club is only positive and significant when accounting for frailty and dismissal probabilities only fall with experience when accounting for frailty. In the quit models, some performance metrics are only significant when one accounts for frailty: recent performance above expectations and promotion last season are only associated with lower quits with frailty, while being relegated last season is only linked to a greater probability of quitting with frailty. However, the overall impression is that unobserved heterogeneity makes little difference to our results (Table 5).

6 Conclusion

Understanding the value of job-matches and the factors leading to their cessation is fundamental to the nature of labour markets. Although initial efforts distinguishing between the determinants of quits and dismissals go all the way back to Farber's

¹² We had initially hoped to run these Cox regressions with shared frailty models, but we were unable to run these as the log profile likelihood was not concave. Hence, we use Weibull regressions instead.

Table 5 Weibull regressions

Variables	(9)	(10)	(11)	(12)
	Dismissal	Dismissal	Quit	Quit
<i>Performance</i>				
League position	1.186*** (0.009)	1.242*** (0.012)	1.065*** (0.013)	1.079*** (0.015)
Surprise	0.598*** (0.023)	0.557*** (0.023)	0.954 (0.047)	0.935 (0.050)
Cum. surprise games 2–5	0.815*** (0.013)	0.805*** (0.015)	0.976 (0.024)	0.975 (0.026)
Cum. surprise games 6–10	0.901*** (0.012)	0.880*** (0.014)	0.967 (0.021)	0.958* (0.023)
Promotion last season	0.946 (0.185)	0.711 (0.174)	0.665 (0.187)	0.581* (0.181)
Relegation last season	0.925 (0.238)	1.091 (0.349)	2.062 (0.911)	2.287* (1.085)
<i>Team experience</i>				
Tenure	0.933*** (0.002)	0.897*** (0.003)	0.946*** (0.003)	0.941*** (0.004)
Tenure squared	1.0001*** (0.000)	1.0001*** (0.000)	1.00009*** (0.000)	1.0001*** (0.000)
Ex player	0.842 (0.104)	0.785 (0.128)	0.706 (0.151)	0.701 (0.160)
Internal appointment	1.013 (0.127)	1.174 (0.211)	0.629* (0.150)	0.634* (0.166)
Num. repeat spells	1.044 (0.109)	1.633*** (0.274)	1.593*** (0.237)	1.783*** (0.329)
<i>General experience</i>				
Experience	0.991 (0.015)	0.946** (0.026)	0.949** (0.023)	0.935** (0.028)
Experience squared	1.000 (0.000)	1.001 (0.001)	1.001* (0.001)	1.002* (0.001)
Num. prev jobs	1.107*** (0.016)	1.121*** (0.032)	1.086*** (0.027)	1.085*** (0.031)
Managing in own country	0.697*** (0.077)	0.663** (0.130)	0.886 (0.150)	0.845 (0.168)
Previous promotion	0.497*** (0.039)	0.450*** (0.061)	0.810* (0.103)	0.791 (0.118)
Prev relegation	1.430*** (0.122)	1.729*** (0.235)	0.828 (0.125)	0.898 (0.158)
Previous championship	0.634*** (0.090)	0.604** (0.141)	1.010 (0.180)	0.987 (0.212)
<i>Controls</i>				
Position end of last season	0.935***	0.925***	0.962***	0.959***

Table 5 (continued)

Variables	(9) Dismissal	(10) Dismissal	(11) Quit	(12) Quit
	(0.005)	(0.007)	(0.010)	(0.011)
Games left	0.961***	0.943***	0.961***	0.957***
	(0.004)	(0.004)	(0.010)	(0.010)
Closed season	27.446***	35.491***	218.984***	224.586***
	(2.751)	(4.039)	(44.251)	(46.046)
Tier2	0.096***	0.049***	0.335***	0.283***
	(0.017)	(0.011)	(0.098)	(0.092)
P (shape parameter)	2.460***	3.729***	2.787***	3.065***
	(0.055)	(0.058)	(0.106)	(0.120)
Theta		1.338***		0.334**
		(0.115)		(0.149)
Constant	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Country dummies	Yes	Yes	Yes	Yes
Season dummies	Yes	Yes	Yes	Yes
Observations	64,495	64,495	64,495	64,495
Number of groups		642		642

Standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Hazard rates are reported to 3 decimal places unless a significant hazard close to 1 required reporting more decimal places

p is the estimate of the natural logarithm of the shape parameter

theta is an estimate of the shared frailty term

(1980) seminal paper, there has been little research on the determinants of quits and dismissals in the intervening period. Instead, analysts have focused their attention on various routes in and out of unemployment, no doubt driven by social welfare concerns to minimise exposure to unemployment.¹³ The exceptions relate to research on CEOs in public listed companies (Gregory-Smith et al. 2009) and the fortunes of sports Head Coaches. Even here it has proved difficult to make the distinction empirically because it is not usually obvious whether a worker has been dismissed or left voluntarily and most data sets are too small to identify with confidence the factors determining the small number of departures which are quits. Nevertheless, it is clear from this small body of empirical research that quits and dismissals are very distinct forms of separation. It is also well-established that poor performance substantially raises the probability of dismissal. Expectations regarding performance

¹³ See for example Bryson and White (1996).

also play a role. For instance, performing below expectations signalled by the betting market predicts dismissal.

Using rich data on Head Coach characteristics, we contribute to the literature by identifying determinants of quits and dismissals across four professional football leagues over the period 2002–2015. We confirm findings from other studies in showing Head Coaches' probabilities of dismissal are significantly lower when the team is performing above expectations, with the effect strongest for recent games. However, in contrast to earlier studies, we find performing above expectations also reduces the probability of Head Coach quits. We also find Head Coach success in the past, as well as Head Coach experience, reduce the probability of being dismissed, even when conditioning on team performance, suggesting Head Coach human capital has some 'protective' effect in managerial careers. Past experience has little effect on quit probabilities – with the exception of tenure at the current employer, which is associated with lower quit rates. Our results are robust to confining estimates to first exits, within-season departures and unobserved Head Coach heterogeneity.

Although we are able to infer something about the nature of Head Coach contracts from the timing of Coach exits we do not observe their contracts and know nothing of their detailed terms. Research that is able to combine detailed information on contractual arrangements with the sorts of data presented here is likely to shed further light on this important if little studied area of labour economics.

Acknowledgements We thank participants at the 2017 Colloquium on Personnel Economics in Zurich, the 2017 Workshop on *Economics and Management of Professional Football* at the Erasmus School of Economics in Rotterdam, the 2016 Football and Finance Conference at the University of Tübingen and the Euro 2016 Workshop on Economics and Football at the University of Reading for valuable comments. We also thank two anonymous referees for their comments.

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Appendix

	League position	Surprise	Cum. surprise games 2–5	Cum. surprise games 6–10	Prom. last season	Relegation last season	Tenure	Ex player	Internal appointment	Num. repeat spells	Experience
League Position	1										
Surprise	-0.0907	1									
Cum. Surprise games 2–5	-0.1557	-0.0095	1								
Cum. Surprise games 6–10	-0.1492	-0.0085	-0.0234	1							
Promotion last season	-0.1368	-0.0093	-0.0133	0.0061	1						
Relegation last season	0.0789	-0.0006	0.0028	-0.0011	-0.0303	1					
Tenure	-0.2474	-0.0087	0.0031	0.0295	0.1082	0.0446	1				
Explayer	-0.0832	-0.0045	-0.0106	-0.011	0.0015	-0.0147	0.1855	1			
Internal appointment	-0.0135	0.0045	0.0073	0.0058	0.0054	0.0054	0.0546	0.435	1		
Num. repeat spells	0.068	0.0002	-0.0047	-0.0123	-0.0211	-0.0247	0.1871	0.1822	-0.0066	1	
Experience	-0.0882	-0.0027	-0.0077	-0.0108	-0.0049	0.0247	0.1554	-0.1773	-0.2933	0.1813	1
Num. prev jobs	0.0217	0.0008	-0.0023	-0.0123	-0.005	-0.0134	-0.0604	-0.2519	-0.3607	0.0867	0.7371
Managing in own country	0.1772	-0.0067	-0.0143	-0.0142	0.0007	0.0166	0.031	0.0366	0.0835	0.0671	-0.0215
Prev promotion	-0.0132	-0.0018	-0.0013	0.005	0.2115	0.013	0.1174	-0.1581	-0.255	0.0305	0.2906
Prev relegation	0.1286	-0.0009	-0.0035	-0.009	0.0117	0.1881	0.0095	-0.157	-0.1914	0.0029	0.2432
Prev championship	-0.3315	0.0107	0.0188	0.0231	-0.0411	-0.0293	0.1609	0.031	-0.0653	-0.0281	0.1746
Position end of last season	0.8073	-0.0035	-0.0113	-0.0224	0.0672	-0.013	-0.2184	-0.0853	-0.014	0.0565	-0.099
Num games left	0.0672	-0.0016	-0.0031	-0.0014	0.0083	0.0343	-0.1381	-0.0198	-0.0225	-0.0306	-0.0192
Closed season	0.0125	-0.0045	-0.0147	-0.0096	-0.0028	-0.0061	0.025	-0.0024	-0.0019	0.0065	0.0106

	Num. prev jobs	Managing in own country	Prev. promotion	Prev relegation	Prev championship	Position end of last season	Num games left	Closed season	tier2
League Position									
Surprise									
Cum. Surprise games 2–5									
Cum. Surprise games 6–10									
Promotion last season									
Relegation last season									
Tenure									
Employer									
Internal appointment									
Num. repeat spells									
Num. prev jobs	1								
Managing in own country	- 0.0088	1							
Prev promotion	0.3469	0.064	1						
Prev relegation	0.346	0.0525	0.2503	1					
Prev championship	0.0206	- 0.2697	- 0.1167	- 0.1134	1				
Position end of last season	0.0106	0.1826	0.0366	0.114	- 0.3561	1			
Num games left	- 0.0093	0.0211	0.0198	0.0056	- 0.0202	0.0456	1		
Closed season	0.0113	- 0.0081	- 0.0043	- 0.0038	0.0002	0.0031	- 0.1656	1	
tier2	- 0.0296	0.155	- 0.0359	0.1254	- 0.2756	0.7984	0.0509	- 0.0007	1

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