Entry, Career Dynamics and Worker Quality in the Labour Market for Talent

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1 Introduction

In many industries firms can only learn about worker quality by observing workers on the job. This is particularly true when worker skills are highly specialized, e.g. in creative industries such as fiction writing, music, sports or academia.[2] At the same time, workers are typically unable to finance their own employment and are therefore unable to reveal their quality to potential employers before entering the labour market. As workers in these industries are often high-profile 'stars', worker quality, once revealed, cannot be kept private by the employing firm. In such a setting firms have to bear the (private) cost of the entrant's potential failure, knowing they will not be able to benefit from the (public) information on worker quality their hiring creates. As a result firms rehire an inefficiently high amount of mediocre experienced workers, i.e. workers which have been revealed to be of low to medium quality, to mitigate the risk of hiring workers of unknown quality. This implies that talent goes undiscovered and there exists 'market failure in the discovery of talent' (see Tervio, 2009).

In this paper we empirically investigate this hypothesis in the labour market for English professional football managers. While previous tests of the inefficient entry hypothesis have looked at field experiments in online labour markets for computer specialists (Palais, 2014) or the role of agencies in online hiring (Stanton and Thomas, 2014), we argue that our setting is particularly suitable to investigate this issue. First, it is very hard to predict the quality of a manager from pre-career observable

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[2] A famous example is J.K. Rowling, the writer of the bestselling series of Harry Potter books, who was refused a publishing contract multiple times before going on to sell millions of books worldwide.

characteristics, a feature which we confirm empirically in our dataset. Second, football managers are very high profile workers such that firms are unable to keep information on worker performance private. Indeed, very few other professions face similar public scrutiny towards job performance. Third, as the number of teams in the English football association is fixed and entry is prohibitively difficult to achieve in the short run, aspiring managers cannot signal their managerial skills to firms anywhere but in one of the incumbent firms in the industry. Finally, the football industry exhibits very clear definitions of success and failure, as winning games is the universal goal of all firms. In other words, our setting is an excellent example of the kind of high profile talent market, where market failure may arise.

Our dataset contains information on every game played in the English football association (the top for tiers of professional English football) during the period 1974-2011. We retrieve financial information, such as wages and transfer spending, as well as information on the board of directors for all clubs from audited accounts filed with Companies House. We combine this with a hand collected database covering personal characteristics (playing career, nationality, age, experience…) for the around 1000 managers, which are active in this period.

As football managers coach their team during multiple games each month, information on their ability gradually improves over time. In other words, firms continuously update their belief on the quality of a particular manager taking his most recent games into account. To identify this information revelation process we develop an estimation algorithm which re-estimates manager quality each month of the sample period. We guarantee robustness of the managerial ability estimates by using both fixed effects estimators in the spirit of Abowd, Kramarz and Margolis (1999), where we are able to control for input use, and several model-free measures, such as a simple comparison of winning percentage with respect to previous managers. We then model firm hiring decisions conditional on the manager quality estimates available at the exact time the decision was made. We use the observed quality of entrants in the five years before the hire to form an estimate of the entrant quality distribution. The comparison of expected entrant quality to the (revealed) quality of a rehired manager at the time of hiring serves as our primary test of the market failure hypothesis. We find strong support for market failure, as about one third of all rehired managers are of lower quality than the median entrant. Furthermore, we find that, as predicted by theory, lower productivity firms both experiment more often (by hiring entrants) and make more 'mediocre' rehires (they hire experienced managers with below median entrant quality) than their more productive counterparts.

Our analysis then proceeds by testing several assumptions which underlie the theoretical analysis. We first test whether a manager's observable characteristics at the time of entry predict his estimated ability well. This turns out not to be the case. Second, we show that higher quality managers show upward career mobility, i.e. revealed high quality workers are poached by larger firms. Hence, smaller firms may rightly fear that the information on manager ability they reveal through hiring will not ultimately benefit them. Finally, we assess the speed of learning by analysing the convergence over time towards stable manager quality estimates.

2 The Setting

2.1 English Professional Football

This paper takes advantage of two features of the market for football managers in professional English football. First, managers compete in an industry which is intensely competitive and the performance of each firm can be assessed with a high degree of accuracy. There are approximately one hundred professional football clubs in England that compete in four hierarchical divisions, an organizational structure which has been largely unchanged for nearly a century. Clubs compete by playing every other club in their division (home and away) each season, with points awarded depending on whether they win, lose or draw. Teams are ranked at the end of the season based on points awarded. Thus an unambiguous ranking of performance is generated at the end of each season. The promotion and relegation system[3] ensures that there is mobility between divisions as well as within divisions, so that over time clubs are potentially in competition with the clubs in all divisions, not just the one they happen to be in during any one season. The objective of any manager is to obtain the highest possible ranking in the divisions.[4]

Secondly, managers are constrained by the resources under their command. Clubs compete to attract the best players giving rise to competitive market in playing talent. The audited annual financial accounts of around 90% of clubs are publicly available and provide detailed information on revenues, expenditures, including wages, assets and liabilities (see for example Szymanski and Smith (1997), Peeters and Szymanski (2014)). Larger clubs tend to command higher levels of support for any given level of success and hence have access to larger budgets. A manager of a club whose annual budget is £100 million is at a significant

[3] Under this system, the worst performing N teams in any division, based on points won during the season, are sent down to play in the division ranked below, to be replaced by the best performing N teams in that lower division. The value of N can vary by division and is occasionally changed. Historically the value has been set at 2, 3 or 4.

[4] Clubs may compete in other competitions such as the FA Cup or the UEFA Champions League, but the principal yardstick for any club is performance in the league divisions.

advantage over one whose budget is £1 million. Using the financial data we are able to control for access to resources.

All football clubs have a “manager”, but the role of the manager in football evolved over time. All professional English football clubs are organized as limited liability companies with a board of directors and CEO responsible for the day to day management of the business. In the early days the board was responsible for the hiring of players and the selection of the team. The role of the manager was mostly to train the players and maintain fitness, as well as organizing travel, laundry, etc. However, the development of tactics in the 1920s and 1930s enabled managers to accrue more control over the running of the team.[5] By the 1970s managers came to exert significant control over the hiring of players as well as the management of training regime, team selection and tactics (on the history of this development see e.g. Carter (2006)).[6]

It is very rare for a football managers to become a member of the board of directors, and so from an organizational point of view one might classify them as “middle managers”. But clearly some football managers rise to positions of great power. The best example in the modern era is (Sir) Alex Ferguson, who was manager of Manchester United from 1986 until 2013 and won 13 league championships, more than twice as many as the second best in the history of English football. Toward the end of his tenure he was considered unsackable and to have complete control over the budget for hiring and firing players. At the other end of the scale, the median tenure in recent decades is about one year. The directors will fire a manager who is not perceived to be successful enough. Perhaps the most extreme example was the case of Roberto di Matteo, who led the club to victory in the May 2012 Champions League final (widely considered to the most prestigious competition in European football) but then fired as manager in November 2012 because the club was not successful enough.

Football managers operate in a very public arena. Every competitive game that teams play is watched by very large numbers of committed fans who engage in detailed assessment of the team and the manager. These views are very widely discussed in the media which devotes a huge amount of space to covering

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[5] Probably the first celebrity manager was Herbert Chapman, who in the 1920s built two teams that went on to dominate the league in the decade (Huddersfield Town and Arsenal). After 1945 Matt Busby at Manchester United and Bill Shankly at Liverpool were powerful figures who further enhanced the status of the manager. By the 1970s the idea of the manager as an individual whose skills dictated the potential of a team, in the same way as a conductor runs an orchestra, was well established.

[6] In North American professional sports such as baseball there is a distinction between the coach, who organizes training and tactics, and the general manager, who is concerned with player acquisition and other administration. These two roles are combined in the football manager.

games. Performance is both observable and opinions are updated on a weekly basis. However, there is little consensus about what makes a good manager, and many of them seem to be eccentric to say the least. For example, one of the most successful English managers in history, Brian Clough, once adopted the bizarre tactic of encouraging his players to get drunk the night before an important Cup final- and his team won.

Our setting closely fits that described in the model of Tervio (2009).[7] First, the clubs operate in highly competitive environment and profits are close to zero or even negative. There is a good deal of insolvency in professional football at all but the very highest levels (Szymanski (2012)), and even the biggest clubs have not reported large profits historically. Second, there is a high degree of turnover among managers, and at any point in time a club can choose between hiring a new entrant and hiring someone who has already been employed as a manager of a professional football club (which we call a rehire). A manager's ability is unknown before they have worked for a club, but once they have been employed their ability can be inferred from the performance of the team that they manage. Unlike the players, who can be tied to a club for at least three years,[8] managers can move at any time. This gives rise to the potential for market failure, in that clubs might be reluctant to hire new entrants who are in expectation better than a mediocre rehire, because the club cannot prevent new hires who turn out to be above average from being bid away by rival clubs. This process will operate differently at different levels of the game. At the highest level (in the top division) we expect rehires to be of higher quality than in the lower divisions, since these clubs are financially stronger.

2.2 Literature

The impact that senior managers have on firm performance is an issue of longstanding interest. IO theory in the 1950s accounted for variations in firm profitability using industry characteristics such as concentration ratios, minimum efficient scale or the advertising to sales ratio. At the same time the development of agency theory (e.g. Fama (1980)) implied that managerial effort and ability could significantly impact performance, if provided with appropriate incentives. Researchers attempted to link corporate pay to firm performance (e.g. Murphy (1985)) but it was not until the work of Bertrand and Schoar (2003) that there was an attempt to directly estimate the impact of managers on firm policies by

[7] Indeed, it may be that professional football may have inspired Tervio's theory. Tervio (2006) considers the problem of player transfers in the football world, and argues that the system helps to ensure market efficiency by committing players to long term contracts, and hence ensuring that teams can guarantee a return on new talent.

[8] According to the transfer rules that currently operate, a player can be traded by his club, but the player has no right to seek another club within the first three years of his contract unless he has just cause (e.g. non-payment of wages) or sporting just cause (e.g. not being able to play regularly).

means of individual fixed effects. Their analysis is based on a sample of about 500 firms and 600 CEOs, all of whom worked for at least 2 firms in the data. They first regress corporate performance variables (e.g. investment, cash holdings) on firm level variables (e.g. Tobin's Q and assets) and managerial fixed effects, to show that these fixed effect significantly influence policy. They then link these effects to individual characteristics of the managers to see how those fixed effects might be affected by personal characteristics. This is the approach we adopt in this paper.

In recent years attention has increasingly focused on the capacity of firms to learn about worker productivity. In particular, employers may struggle to distinguish between established ability which can only be learned by experience and time-varying worker productivity (see e.g. Kahn and Lange (2014)). Whereas Lange (2007) finds that employers learn fairly quickly- based on an annual survey employers reduce initial expiration errors by 50% within 3 years, other papers, for example, Kramarz and Nordstrom Skans (2014) show that social ties are still important channels to allow employers to vet workers before entry into the workforce.

Tervio (2009) provides the theoretical inspiration for our contribution to this literature. Tervio models the labour market for highly skilled individuals assuming that ability is unobserved ex ante but is revealed on the job. In a two generation model he shows that experienced workers will be able to extract all rents from their employment, so that only above average workers are retained, and below average workers are replaced by new entrants. However, the exact threshold for firing depends on the ability of firms to recover losses on unprofitable hires. If workers can pay for their jobs there exists an efficient threshold with the socially optimal level of retention; however, if entrant workers are capital constrained there will be too much retention, and in particular some workers will be retained even though their known ability is lower than the expected ability of an entrant. In this paper we test for inefficient retention of football managers.

Sports such as football provide an ideal "laboratory" for testing labour market theories (see. Kahn (2000)). There are many competing firms but the industry is relatively homogeneous, and indicators of success are largely unambiguous (e.g. winning). There are many chances to observe productivity since each firm plays many games in a season. Interest in the outcome of competition is intense and closely observed.

There is already an extensive literature on managers in sports, most of which is focused on football (soccer). To be clear, "manager" in this context means the person in charge of determining team tactics, selecting the team, coaching and the hiring of players – typically answerable to the board of directors, and often directly to the owner. The literature has focused on two main questions. First, what determines the probability that a manager will be fired, and what are the consequences, e.g. Audas et al (1999), Bachan et al (2008), Barros et al (2009), Bruinshoofd and Ter Weel (2003), d"Addona and Kind (2014), De Paolo and Scoppa (2011), Frick et al (2010), Koning (2003), Forrest and Tena (2007). A key issue for these papers is that managers are typically fired when performance is poor and team performance typically improves after the manager is fired, but since performance is subject to exogenous shocks, it is not clear that these changes are in fact attributable to the manager. In a recent paper Van Ours and Tuijl (2016) looked at the dismissal of manager in Dutch football and developed a control group of teams with similar performance but which did not fire their managers. They found that performance falls before and rises after dismissal, but not significantly differently from the control group.

The second focus of the literature has been the estimation of managerial ability. These papers have tended to rely on season long, rather than game-by-game measures of performance (which we use) and therefore have too few observations to run a fixed effects model. Bridgewater et al (2011) use a stochastic frontier model to estimate influence of managerial characteristics on performance in the four English professional football divisions over the period 1994 to 2007. They find that managers (most of whom are former players) in the highest division (the English Premier League) tend to have a larger impact on team performance when they themselves played at a higher level, but this only applies to the better teams. Del Corral, Maroto and Gallardo (2015) use a stochastic frontier model to estimate the impact of coaches in Spanish basketball and foreign coaches perform better than domestic ones. Goodall et al (2009) find that coaches in US basketball who have been players perform better and that and better players make better coaches (which they attribute to expert knowledge acquired in the playing career). Frick and Simmons (2008) use a stochastic frontier model to estimate team performance in German football as a function of wages paid to both the players and the manager. Bell et al (2013) use a fixed effects model to estimate managerial ability but covering a relatively short period of time (five seasons) and a small number of managers (60) and do not allow for the estimated fixed effects to change over time.

3 Data and Empirical Framework

3.1 The data

In most activities performance measurement is difficult and often imprecise. In football performance is measured by the outcome of games played and in particular the number of goals scored and conceded. A manager's career can stretch over hundreds and possibly thousands of games, and for each game there is no uncertainty about performance as measured by goals scored and conceded- the outcome is a matter of official record. In each season a club plays in the region of 40 league games, and our data covers the 38 seasons from 1973/74 to 2010/11 across the four professional English divisions, yielding a total of over 50,000 games played.

Our data includes all identified club managers, over 1000 in total, of which over 870 end up in the final sample. Because of their significance to the success of the team, managers are closely scrutinized and their careers are well documented. Basic personal details such as age and origin are well known. In addition most managers are selected from the ranks of former players and data on their playing careers is also readily available.

A club such as Manchester United attracts home crowds of over 75,000, while the average team competing in the fourth tier attracts an average of less than 5,000 fans per game. These large differences are reflected in the revenue generation of clubs, and their capacity to spend on playing talent, which in turn influences the probability of winning games. The market for players is highly competitive with many buyers and sellers and a good deal of information available on ability based on observed performance in games.

Because all clubs are limited liability companies registered in the UK, and because all registered companies have to deposit a copy of their independently audited financial accounts with Companies House, a public agency which then makes the filings available to the general public, we are able to assemble comparative financial statistics for almost all the clubs. Accounts in one form or another were filed for 95% of the clubs in our data, including data on wage expenditure for 85% of clubs. Previous research (e.g. Peeters and Szymanski (2014)) has shown that there is a high degree of correlation between wages and team performance.

3.2 Empirical framework

3.2.1 The hiring decision

In our empirical analysis we model the hiring of a manager by the board of club i conditional on information available at the time of hiring t. We assume the board's objective is to hire the manager with the highest estimated quality, who is still willing to join the team. The team has two options, either rehiring a manager, m, which has already been active in the football industry, or hiring an entrant, e.

If it rehires an experienced manager, an estimate of the manager's quality, $\hat{q}_{mt}$, is available to the club.[9] The board then hires the manager with the highest quality estimate in the pool of available managers.

[9] Although not necessarily to the econometrician, see below.

Clubs in lower divisions are typically unable to attract high quality experienced managers, because they lack the financial muscle to meet the manager's demands both in terms of personal compensation and investments in the playing squad. This implies that the quality of the available experienced managers varies for teams in different divisions, with the fourth and third division teams facing the lower end of the quality distribution. We hence allow the maximum obtainable quality to differ by division, $\hat{q}_{dmt} = \max_d[\hat{q}_{mt}, \hat{q}_{-mt}]$. We further assume that the accuracy of the quality estimate increases in the amount of experience the manager has up until t, as every additional game allows the club to refine its assessment of the manager's talent. We allow for the possibility that the club derives more information from a game managed in England than from a game managed abroad and therefore distinguish between a manager's experience in England, e_{mt}, and abroad, a_{mt}.

If the team hires an entrant, it has no way to infer the quality of the individual manager e. In this case, the club forms an expectation of the manager's quality based on the distribution of estimated qualities for all other entrants in the n periods leading up to time t, i.e. $\hat{q}_{et} = E\left[\hat{q}_{-et}\right]_{t-n}^{t-1}$. We later discuss several ways in which the club may form its expectation based on the observed distribution of estimated entrant qualities.

The pay-offs associated with decision problem for a club i playing in division d at time t are given as

$$P(H_{idt}) = \begin{Bmatrix} \text{if } H_{idt} = e\text{:}\ \ \hat{q}_{et} = E[\hat{q}_{-et}]_{t-n}^{t-1} \\ \\ \text{if } H_{idt} = m\text{: } \hat{q}_{dmt} = \max_d[\hat{q}_{mt}, \hat{q}_{-mt}] \end{Bmatrix}. \tag{1}$$

A couple of predictions, which mimic the theoretical insights of the model in Tervio (2009), follow directly from observing equation (1). First, lower productivity firms (here, in terms of division), hire more labour market entrants, because they lack access to the most talented incumbents. Furthermore, lower productivity firms also have a higher probability of hiring an incumbent with an estimated quality below the median entrant. Following Tervio (2009), we dub these incumbents 'mediocre', although our definition is slightly different from his.[10] A final thing to point out here is the role of manager experience in this framework. As teams observe more games coached by an incumbent manager, the precision of their quality assessment improves. This implies that the probability of a mediocre manager getting rehired should decrease in the manager's experience. Whereas clubs may mistakenly overestimate a manager's

[10] In Tervio (2009) a rehired incumbent is dubbed 'mediocre' whenever social welfare would be higher had that incumbent been replaced by an entrant. Our definition is therefore slightly starker.

quality based on the limited observations available early in his career, this should no longer occur as estimates get more and more precise.

As information on managerial quality is revealed gradually over time, our analysis of the club's hiring decision should condition solely on information the club had access to at the time of hiring t. To this end, we develop an estimation algorithm which allows to evaluate each manager's quality at time of hiring.[11] After a manager's entry into the dataset our algorithm re-estimates his quality at the end of each calendar month, apart from June and July in which there is no league play. This implies that we update our quality estimate for every four to five games the manager coaches. As such, we exploit the amount of observations per worker we have at our disposal, to obtain a profile of monthly quality estimates over a manager's career rather than just an end-of-career estimate.[12] To model the club's decision problem, we analyse the hiring decision at time t based on the quality estimate at the end of the preceding month. In a similar fashion we produce monthly updates for our estimate of the entrant quality distribution. Our estimation algorithm has the further advantage that it allows to test several assumptions underlying the theoretical results in Tervio (2009). For example, we examine how unpredictable worker quality is pre-entry by assessing how well pre-career characteristics predict revealed manager quality. Along the same lines, we look into the speed of employer learning by investigating how informative early career quality estimates are of later assessments.[13]

3.2.2 Assessing manager quality

A next step in the empirical analysis of the hiring problem is obtaining estimates for $\hat{q}_{mt}$, i.e. the quality assessment of manager m conditional on information available at time t. Our primary definition of manager quality is based on the estimation of person fixed effects, as pioneered by Abowd et al. (1999).[14] In our case, we estimate a model explaining the goal difference, y_{ijt}, in a game between clubs i and j at time t. We relate this to a vector of logged inputs for each club (X_{it} and X_{jt}), a set of firm fixed effects (γ_i and γ_j) and individual manager fixed effects (μ_{mi} and μ_{mj}). Our baseline model is given as:

$$y_{ijt} = \beta_d X_{it} - \beta_d X_{jt} + \gamma_i - \gamma_j + \mu_{mi} - \mu_{mj} + \varepsilon_{ijt}. \tag{2}$$

[11] A typical club plays four to five games in each month of the season.
[12] Note that we use the first 10 seasons in the data as a learning period and start the analysis of hiring in August 1983.
[13] We will abstract from the possibility that worker productivity may be evolving over time. See Lange (2007) and Kahn and Lange (2014) for further analyses of employer learning, which take this feature into account.
[14] Abowd et al (1999) apply employer and employee fixed effects to the estimation of individual wage equations and develop an identification strategy based on moving employees. While we apply the same identification strategy, our focus on firm output measures is probably more closely related to the analysis of Bertand and Schoar (2004).

We allow the coefficients on variable inputs to differ by the division the game is played in. A first term in vector X_{it} is a dummy denoting the home and away team, which is relevant because of the persistence of home advantage in professional team sports. As in Peeters and Szymanski (2014) we control for the player inputs at the manager's disposal by means of the total wage bill paid out by the club in season t. We further include the book value of tangible fixed assets to proxy the value of the stadium and training grounds, which is the only relevant tangible investment clubs have on the books. To address concerns about potential feedback effects from results to inputs, we run each of our models twice, once using current input choices, and once using past payroll and assets to instrument for current values. We then report the correlation of manager fixed effects across all approaches below.

Recently, several papers have voiced concerns over the importance of the firm-worker match value to the estimation accuracy of firm-worker fixed effects, as laid out above (see Jackson, 2013 and Peeters et al, 2015). Here, we rely on two techniques to separate manager and club effects. First, we apply the two-stage fixed effects method introduced by Jackson (2013). We estimate firm-worker spell fixed effects in the first stage, and split these into worker and firm effects using weighted least squares with inverse first stage standard errors as weights. This method forces a mean zero assumption on the match quality of all spells a worker has over his career in the data, but allows for differing match qualities among his spells. We refer to these estimates as 'Spell FE' in the remainder of this paper. Alternative methods we consider to split out the spell effects are (a) to use non-weighted least squares in the second stage and (b) to report the individual firm and manager average, weighing the spell values by the number of observations the individual has in each of them. In a second approach (dubbed 'FE') we revert to the standard FE method and introduce manager and firm dummies in the estimation of (2), relying on moving individuals to separately identify the person and firm FEs. Worker-firm match values are then incorporated in the error term.

In order to circumvent further concerns related to the econometric analysis laid out above, we also introduce a cruder measure of managerial quality, 'added win%', which requires no formal econometric analysis. Here we define managerial quality, wp_{mt}, as the average winning percentage a manager m realizes at all teams i in division d relative to the historic winning percentage of those teams i at level d before manager m's arrival ($\overline{wp}_{-mid}$). More formally, we specify that

$$wp_{mt} = \sum_{g=1}^{g=n_t} \frac{1}{n_t}\left(w_{gmid} - \overline{wp}_{-mid}\right), \qquad (3)$$

where n_t refers to the number of games the manager has been active up until time t and w_{gmid} is the result of game g, coached by manager m at team i in division d expressed as 1 for a win, 0.5 for a draw and 0 for a loss.

To aid the interpretation of the effects we find in further analyses, we standardize all manager quality measures by subtracting the mean quality estimate in the manager population at time t and dividing the result this by the population standard deviation.

3.3 Manager quality initial results

Tables 1-3 summarize our estimates of managerial quality for our different estimation techniques as well as the personal characteristics of the manager. Table 1 shows the means for the full sample and by quartile given the number of periods in the dataset. It shows that managers will more experience tend to have higher quality, whether measured by spell fixed effect, fixed effect or by added win%. Managers in the highest quartile are present in the data for an average of 107 periods (one period is a month, and the playing season lasts 10 months, so this amount to a career of just over 10 years), while in the fourth quartile experience averages 5 periods, or just half a season. Experienced managers tend to be older and are more likely to be foreign. They are more likely to enter as a player-manager, less likely to be an internal hire and more likely to start at a higher division. They are also more likely to have been a professional player, to have played for a team in the big four leagues, but not more likely to have played for their national team.

Table 2 compares the average quality estimate and personal characteristics of all managers at the end of a spell and rehires at the beginning of a new spell. This shows that the quality estimates of managers about to end a spell (whether fired, quitting or retiring) is lower than the quality estimate of a rehired manager. In terms of individual characteristics there do not appear to be large and predictable differences. In general this is consistent with a story in which failing managers separate from their club and are replaced with better managers.

In Table 3 we report the correlation between our measures of manager quality at the level of the individual manager. As it turns out, our measures are highly correlated. This is particularly true for the various methods we employ for the ‘spell FE’ estimates, but even when we resort to the relatively naïve assessments of the added win percentage, we still find a correlation above 0.6. Given these results, we will further on report results for only three sets of quality measures, the baseline “spell FE”, “FE” and “added win%”.

For purposes of illustration it is useful to provide some examples of our quality estimates by looking at some examples of managers who are well-known if football circles, and we do this in figure 1. The top left hand panel compares data for probably the three best known managers in our sample, Sir Alex Ferguson (manager at Manchester United in our data), Arsene Wenger (Arsenal) and Jose Mourinho (Chelsea). Ferguson had the longest career at a single club of any manager in the history of English football (26 years), Wenger's career at Arsenal began in 1996, while Mourinho was at Chelsea for a relatively short spell, 2004-2007 (our data does not include his more recent return to the club). Ferguson's fixed effect is significantly different from zero and marks him as one of the most able managers in English football, but what is also noticeable is that his fixed effect falls after a good start and then rise consistently but only after 6 years of experience has been accumulated. Wenger, by contrast has a consistently higher fixed effect. This might seem surprising since Ferguson has won far more trophies, but the difference can be explained by the fact that Ferguson always had considerably greater resources to spend on players throughout the period.

The second panel compares Wenger to his predecessor at Arsenal, George Graham. They both won two league titles while managing the club, and therefore might be thought to be of comparable quality- but in fact our estimates suggest that Wenger has been on average of far higher quality. This appears to be confirmed by the fact that Graham went on to manage Arsenal's local rivals, Tottenham, after leaving Arsenal, and still generated a fixed effect well below Wenger's. Once again the most likely explanation is that Wenger has achieved success on a far tighter budget than comparable managers.

Finally, the third panel compares Ferguson to Kenny Dalglish, who took over as player manager at Liverpool in 1985 and led the club to three championships before leaving the club in 1991, then managing Blackburn Rovers between 1991 and 1995, including winning the Premier League title, then had a less successful spell at Newcastle in 1997/98, and finally returned for a brief spell at Liverpool in 2010/11. Our estimation does not enable us to estimate a fixed effect for Dalglish since we have no Liverpool managers to compare him against in his early years of tenure, so instead we compare Dalglish and Ferguson using our other measure, added win percentage. This comparison shows that for the first few periods (months) both managers had significantly rising added win percentage, suggesting that they were outperforming previous managers, but that Ferguson failed to sustain this performance in the early years while Dalglish did so both at Liverpool and subsequently at Blackburn, before beginning to decline at Newcastle. Ferguson, however, once he had bottomed out in the early 1990s (when he was almost fired) he sustained an extraordinary and consistent increase until the end of his career, by the end of which he was widely acknowledged to be the greatest manager ever to work in the English game.

4 Main results

4.1 A significant fraction of rehires are mediocre

Tervio's model predicts that firms will underinvest in hiring new talent, which will result in "too many mediocrities populating the industry". In our setting a mediocrity is defined as an experienced manager whose performance is estimated to be inferior to the median expected performance of an inexperienced manager. We therefore interpret the theoretical prediction to mean that firms will tend to rehire significant numbers of mediocrities.

This prediction is supported by the data. Table 3 shows the proportion of rehires that are mediocre, depending on the estimation method and the division in which the club played when the manager was hired. The three estimation methods shown in the table are "spell fixed effects" – where we estimate the manager's productivity independently of the club, "fixed effects" – where no separate club productivity parameter is estimated, and "add win%" which is estimated simply on the basis of the success of the club under the manager's tenure without any additional controls. For each estimate there are two bases for comparison- "median 5 year" compares estimated productivity with all managers over the previous 5 years, while "median 5 year in div." compares only with the 5-year performance managers currently in the same division.

Thus the first row of table 3 tells us that in the full sample there are 701 cases of new entry (inexperienced managers) and 756 cases of rehires. For the average rehire there were 96 examples of new entrants in the previous five years. The experience of these new entrants, we argue, should have set expectations about the productivity of a new entrant. In 188 cases (24.9%) the rehire was of lower estimated quality than could have been expected of an entrant.

Figure 2 illustrates the estimated efficiency of rehires relative to the median entrant. The horizontal axis is measured in standard deviations. To be consistent with Tervio's theory a majority of rehires should be above the median entrant (otherwise there would be no learning) but a significant minority of rehires should be below the median, as is clearly the case.

4.2 Which firms rehire mediocre managers?

Table 3 shows that we obtain similar results regardless of the estimation method (Spell FE, FE or add win%), but it also shows that clubs in the lower divisions are more likely to make a mediocre rehire. Thus in the spell FE model, comparing rehires with the median entrant across all divisions, 14.7% were mediocre in the top division, 18.7% were mediocre in the second division, 30% in the third and 34.8% in the fourth.

The lower the division, the greater the number of entrants, but still larger is the number of mediocre rehires.

In Tervio's model the output of the firm is proportional to the quality of the manager at equilibrium. Given the zero profit constraint, any firm can either hire an experienced skilled manager and generate a large output, or hire a low quality experienced manager and generate low output, or hire a new entrant and generate an expected output equal to the average quality of entrants. Output is sold at a single market price and wages for experienced managers exactly reflect their ability.

In our context firms operate at different levels, even if the system of promotion and relegation allows some mobility between levels. Each firm produces the same quantity of output in the sense that the number of games played in a season is more or less identical, but prices tend to be higher (e.g. ticket prices and broadcast rights) and fan interest tends to be greater in the higher divisions. The industry is highly competitive, characterised by persistent loss-making and insolvency.[15]

Given these characteristics we expect that (a) the quality of experienced managers is likely to be greater in the higher level divisions and (b) that entrants will be more likely to enter in the lower divisions. Table 3 confirms that most entrants start in the lower divisions.

In Tervio's model there are two generations of workers with equal numbers in each cohort, the same ability distribution and hence the same average ability. If ability can be observed after obtaining some work experience, then only the best workers in the first cohort are rehired and hence unless all of them are rehired the average ability of a second generation worker (with unknown ability) is lower than the average ability of the first generation. Hiring a second generation worker delivers an expectation of a worker with average ability, so any rehired worker of above average ability is better. Suppose exactly half of all workers in the first generation are retained, then every new hire is worse in expectation than each of the retained workers. Absent financing constraints, new hires would pay to obtain a job that would then deliver rents in their later career. Indeed, they would be willing to pay up to their expected rents in the second stage of their career, raising the threshold for rehiring first generation workers above the average ability. The inefficiency arises in Tervio's model because workers may have financial constraints which limit their ability to pay for jobs, and so firms may prefer to hire experienced workers whose ability is above average but below the efficient threshold. These are the managers he defines as mediocre.

[15] See Szymanski (2015) for a detailed financial analysis of English football.

Tervio's model assumes a continuum of workers whereas obviously we are working with a discrete number of individuals. Thus we define a mediocrity as anyone whose measured ability is below the median. In Tervio's framework it would never make sense to rehire a worker with below average ability, since the expected return on a new hire would be greater. In our case most rehired managers are not far below the median and the mean ability (e.g. measured by the spell fixed effect) of our mediocrities is usually close the mean ability of entrants. However, we also think that other factors may enter the decision making process. Given that a bad managerial choice could result in relegation and financial collapse, it may be preferable to rehire a below median manager of known ability than an unknown quantity. This is essentially a problem of financial constraints faced on the side of the firm, as opposed to financial constraint on the part of the worker found in Tervio.

These financial constraints are more severe in the lower divisions than they are in the higher divisions. In our sample there were 17 cases of clubs entering legal insolvency proceedings while playing in the second division, 49 cases where the clubs was in either the third or fourth division, but only one case where the club was in the highest division (see Szymanski (2012) for more details). This may explain why the fraction of mediocrities rehired increases in the lower division. The robustness of this result is demonstrated in the two lower panels, which show that for quite different estimation procedures (fixed effects and added win percentage), the same pattern emerges: about one quarter of rehires are mediocre and the proportion increases in the lower divisions.[16]

4.3 Are mediocre rehires underperforming?

Learning is possible, even for football managers. Therefore were examined performance of managers from one employment spell to another, to see if their estimated quality changed. In particular, we wanted to see if mediocre managers stayed mediocre, or if hiring a mediocre manager could be justified by the expectation of improved performance.

Table 5 reports the transition probabilities of managers rated mediocre or "good" at the end of any spell. As before we report three different models (spell fixed effects, manager fixed effects and added win%) and measure mediocrity relative to all entrants in the sample or entrants in the same division as the rehired manager.

[16] See also Table 6, which is a regression of the rehire probability for mediocre managers based on individual and club characteristics. A mediocre manager is more likely to be rehired in the third and fourth divisions.

We find that between 29% and 34% of managers rated mediocre at the end of a given spell become “good” by the end of their next spell. Thus in general two thirds of mediocre managers stay mediocre. By contrast, between 86% and 91% of managers rated “good” at the end of a given spell are still “good” at the end of the next spell.

Thus we conclude that managerial quality is fairly well identified at the end of the first spell and there is limited tendency for individual productivity to grow over time. Since mediocre managers are inferior to the median entrant, and only one third of them are likely to move out of this category, it really does appear that the median entrant would deliver a better expected performance than a mediocre rehire.

Table 6 uses a linear probability model to estimate some of the factors that explain mediocre rehiring. The dependent variable is a dummy variable for mediocrity defined by the spell fixed effect of a rehired manager relative to the median entrant over the previous five years. The first column shows that the probability is decreasing in the number of games that the manager had been in charge in his previous spell. Non-England games refer to the number of games that the manager had been in charge when managing teams outside England (either an English manager working abroad or a foreign manager). The remaining columns estimate variant of the model, and show that the probability of mediocre rehires is always decreasing in experience, and the coefficients appear to be stable.

The second column uses all observations instead (in some cases we do not have all the data for all games played, so total observations are smaller than total games in charge). The third column breaks the data down into bins, and shows that the probability of a mediocre rehire decreases with higher levels of experience. The last three columns includes both characteristics of the manager (age and nationality) and the division in which manager worked. The columns differ according the controls included (entry mode, playing career and monthly fixed effects). They all tell a similar story. As mentioned before, mediocre rehires are more likely in lower divisions. Also, foreign managers are less likely to be mediocre rehires (this might suggest a preference for English managers at the expense of ability).

5 Testing the model assumptions

Following Tervio (2009) we argue in this paper that the market for football managers is characterized by a market failure, namely that mediocre managers (defined as managers whose performance is worse than median entrant) are consistently rehired. For this to make sense it has to be the case that the ability of entrants is noisy but that experience reliably reveals managerial ability and that revealed high quality workers can be poached by the more productive clubs. We now discuss our testing in support of these conditions.

5.1 Worker quality at entry and the speed of learning

Even when managerial ability may not be observed, a good deal is known about most managers at the beginning of their career. In terms of relevant experience, over 95% of managers in our sample are former professional players, and indeed 29% start their managerial career while still playing. In terms of playing experience, the most prominent leagues (at least to an English audience) are the top division in England together with the top divisions of Spain, Germany and Italy, and almost two thirds of managers has experience in one of these leagues, while 37% played at international level (i.e. represented their country in international football competition). As expected, most managers acquired their experience in England, having played for between 3 and 4 English clubs on average. We also observe the way managers enter the market. Apart from the player-managers mentioned above, about 35% are internally hired, i.e. they were promoted to the top job from another managerial role within the club. Further characteristics such as age and nationality are easily observed as well.

To examine whether manager ability is predictable at the time of entry into the labour market, we relate revealed quality after the 10th period the manager is observed to a vector of observable entrant characteristics. Our model for entrant quality reads

$$\hat{q}_{mt+10} = \beta_x X_{mt} + \varepsilon_{mt}, \tag{4}$$

where the vector X_{mt} includes the manager's personal characteristics at the time of entry. In our baseline model this includes log manager age, its square and triple, the log period of entry, a dummy for foreign managers and all variables in Table 3 which refer to his playing career and labour market entry. We find however that none of the models based on these characteristics reaches an R-squared value of 0.1 for any of our ability measures.

Next, we assess how quick clubs may learn about manager ability. To this end, we revisit (4) but add the current quality estimate as a regressor to predict future quality estimates, i.e.

$$\hat{q}_{mt+10} = \beta_x X_{mt} + \beta_q \hat{q}_{mt} + \varepsilon_{mt}. \tag{5}$$

Now we ask how the adjusted R-squared of this regression evolves as managers are observed over an increasing number of periods. To assert robustness against selection bias (suppose for example that surviving managers are easier to predict), we repeat this exercise both for the entire sample (no selection) and a subsample of managers with at least 50 observed periods (selection). In the case of the spell fixed effect we also experimented with a 5 period lag. The results are illustrated in Figure 3. Clearly, when the manager has no managerial experience, the adjusted R^2 of the regression starts of close to zero in each case. Within 10 to 20 months it rises to about 80%, after which it continues to trend slowly toward unity. We interpret this to mean that managerial ability is unpredictable at the start of the managerial career, and hence individual entrant quality is hard to predict. At the same time, experience reveals ability relatively quickly, i.e. within the first two years.

5.2 Revealed manager quality and career progression

Next, we examine whether managers with higher revealed ability, are prone to being pooched by more productive clubs. We test this by assessing the impact of revealed ability on the manager's career progression. First, we show that higher estimated managerial quality increases the probability of being rehired. To this end estimate a probit model relating the fact that a manager is rehired by another team after the end of his spell at time t, y_{mt}, using the estimated manager quality at time t and a vector of personal characteristics X_{mt} as explanatory variables, i.e.

$$y_{mt} = \beta_x X_{mt} + \beta_q \hat{q}_{mt} + \varepsilon_{mt}. \tag{6}$$

Table 7 reports the model estimates for our sample. The first three columns use our three different quality estimates - the spell fixed effect, fixed effect and added win % for all rehires, and the quality estimate is significant at the 1% level in all three cases. Columns (4)-(7) uses our preferred quality estimate, spell fixed effect, and adds the extra controls. Column (4) includes the average win% of the manager, while columns (5)-(7) also include the number of games as a manager, age, nationality and the other controls for entry method and playing career listed in Table 3. Managers with more experience in games are more likely to be rehired, while older managers are less likely to be rehired. Foreign managers are more likely to be rehired although this effect is not significant in all specifications. Overall, the impact of managerial quality is robust to changes in specification- clubs are able to select and re-hire more able managers.

Second, we fine tune our model to look closer into career progression. We replace the rehire dummy in (6), by an ordered variable taking value -2 if the manager is never rehired again, -1 if he is rehired in a lower division than where his spell ends, 0 if he is rehired in the same division and +1 if he is rehired in a better division.[17] Table 8 shows the ordered probit results for this career progression model. The columns

[17] We treat the big 4 as equivalent to the 1st English division, and other foreign leagues as equivalent to the 2nd division.

are defined in the same way as in Table 7 using the same variables. Indeed the results appear similar. The probability of a rehired manager working in a higher division is increasing in all variants of the quality estimate and is robust to changes in specification.

6 Discussion and conclusions

Recent research has focused on the efficiency of labour market dynamics – do entrants have a chance to establish themselves in the market when faced with experienced insiders? This is an important policy question given the problems of youth unemployment and the potential waste of resources involved. Theory has suggested a number of frictions which may present obstacles, particularly in markets for high skilled workers where ability may become apparent relatively quickly and so employers have a reliable point estimate to compare against an entrant distribution. This paper exploits a rich dataset in a particular talent market to compare the ability of managers who are rehired against entrants. We find that the market works, in the sense that better managers tend to survive, get rehired, and get promoted to better jobs. Employers have limited information about the potential of entrants and cannot easily use known characteristics to screen individuals, but once on the job employers can learn quickly, and our evidence suggests that they use this information. Against this background of a functioning market, we find evidence of market failure, in the sense that a significant fraction of rehires are inferior to median entrant. Thus our research supplies empirical support for the theoretical models of market failure in highly skilled labour markets.

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8 Tables and Figures

Figure 1: Manager quality estimates over time for selected managers

Figure 2: Distribution of rehired manager quality estimates minus 5 year median entrant quality estimates

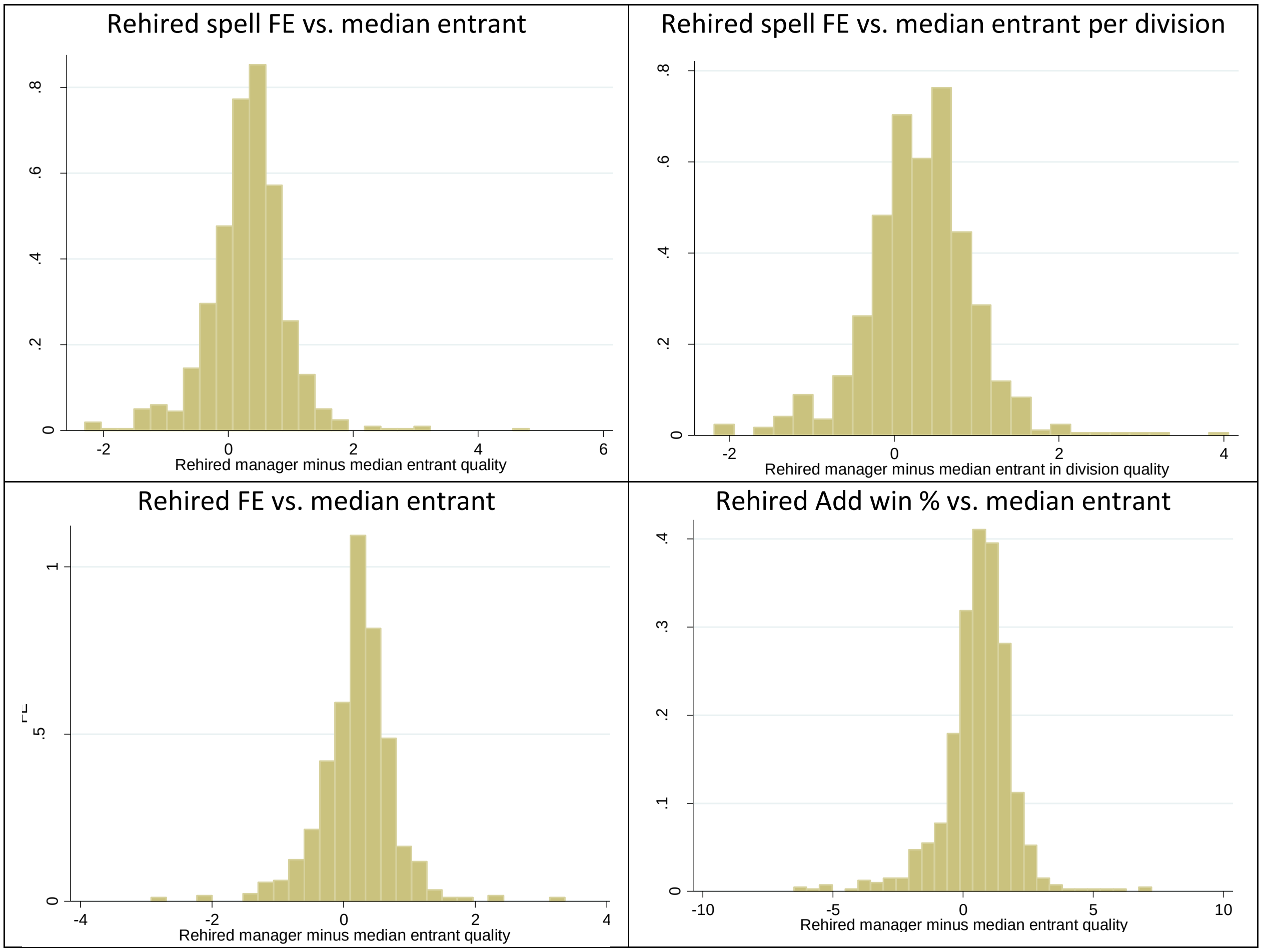

Figure 3: Adjusted R-squared for regression of quality measures on manager entry characteristics and 10- or 5-period lagged quality measure, by observed period

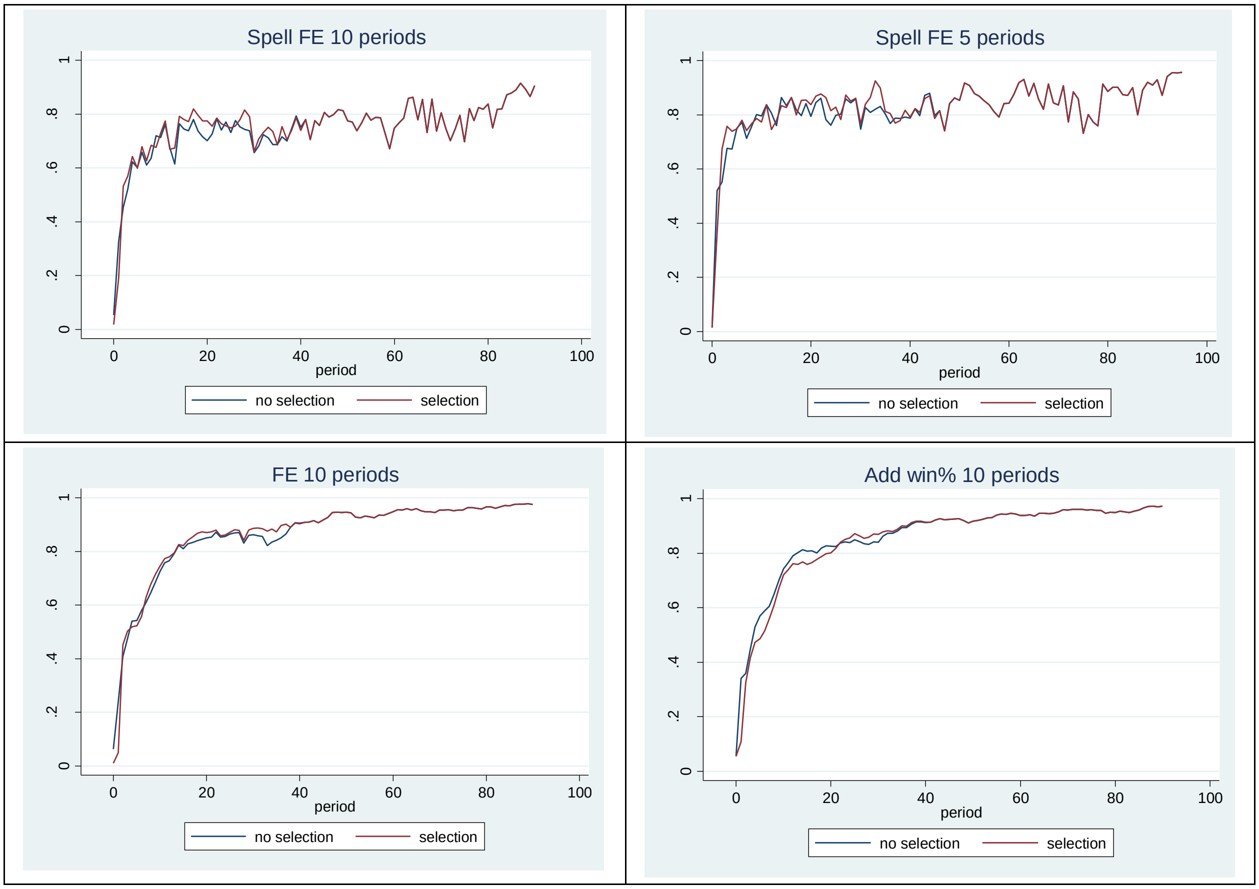

Table 1: Correlation among quality estimates at manager level

Correlation Coefficient	FE	Add win%	Non-weighted spell FE	IV 1st stage	Av. Spell FE	Av. win %	Av. Goals pro
Spell FE	0.901	0.604	0.999	0.967	0.834	0.551	0.468
FE		0.672	0.895	0.839	0.824	0.608	0.506
Add win%			0.601	0.593	0.683	0.847	0.646

Table 2: Summary statistics at individual manager level by quartile in number of periods present in dataset

Periods present:	Full sample			Quartile 1			Quartile 2			Quartile 3			Quartile 4		
Variables	**Obs.**	**Mean**	**St. Dev.**	**Obs.**	**Mean**	**St. Dev.**	**Obs.**	**Mean**	**St. Dev.**	**Obs.**	**Mean**	**St. Dev.**	**Obs.**	**Mean**	**St. Dev.**
Quality Measures															
Spell FE	580	0.110	0.778	106	-0.088	1.127	115	0.011	0.778	161	0.129	0.726	198	0.259	0.523
FE	580	0.275	0.747	106	0.067	1.081	115	0.235	0.745	161	0.291	0.690	198	0.396	0.519
Add win %	673	-0.250	1.630	150	-0.983	2.581	144	-0.517	1.335	178	0.047	1.182	201	0.227	0.831
Periods present	873	40	47	243	5	3	198	15	4	217	36	10	215	107	47
Obs. FE	580	92	108	106	8	5	115	24	9	161	57	31	198	206	113
Obs. Win%	679	100	112	152	11	6	147	33	11	179	78	33	201	236	114
Manager Char.															
Av. Age (day)	860	15621	2393	232	15486	2854	197	15184	2467	216	15428	2168	215	16362	1766
Av. Exp. (game)	873	136	165	243	64	153	198	81	139	217	123	117	215	280	150
Av. Eng. Exp. (game)	873	109	140	243	27	92	198	53	98	217	96	81	215	267	137
Foreigner	873	0.058	0.235	243	0.086	0.282	198	0.061	0.239	217	0.065	0.246	215	0.019	0.135
Market Entry															
Player-manager	868	0.290	0.454	239	0.243	0.430	197	0.254	0.436	217	0.295	0.457	215	0.372	0.484
Other man. exp.	867	0.525	0.500	238	0.571	0.496	197	0.569	0.497	217	0.493	0.501	215	0.465	0.500
Intern hire	867	0.347	0.476	238	0.450	0.498	197	0.350	0.478	217	0.326	0.469	215	0.251	0.435
Division	873	2.759	0.984	243	2.815	1.082	198	2.960	0.980	217	2.764	0.944	215	2.508	0.854
Playing history															
Play prof.	872	0.953	0.212	242	0.913	0.282	198	0.965	0.185	217	0.968	0.177	215	0.972	0.165
Play big 4	872	0.658	0.475	242	0.599	0.491	198	0.677	0.469	217	0.645	0.480	215	0.721	0.450
Num. Eng. Team	873	3.480	2.301	243	3.432	2.537	198	3.606	2.312	217	3.392	2.305	215	3.505	1.998
Ex-player club	873	0.447	0.451	243	0.531	0.498	198	0.461	0.486	217	0.465	0.449	215	0.319	0.323
International	872	0.374	0.484	242	0.326	0.470	198	0.359	0.481	217	0.438	0.497	215	0.377	0.486

Table 3: Summary statistics at spell level for sample of ending employment spells and rehires

Variables	Ending Employment Spells					Starting Rehire Spells				
	Obs.	**Mean**	**St. Dev.**	**Min.**	**Max.**	**Obs.**	**Mean**	**St. Dev.**	**Min.**	**Max.**
Quality Measures										
Spell FE	1,460	0.104	0.855	-4.745	4.648	757	0.256	0.626	-2.429	4.626
FE	1,460	0.261	0.810	-4.511	3.947	757	0.375	0.570	-2.748	3.467
Add win %	1,680	-0.376	2.003	-8.136	7.468	819	0.043	1.347	-6.957	6.659
Obs. FE	1,460	160	178	1	1045	757	195	176	1	1033
Obs. Win%	1,686	177	189	0	973	828	219	185	0	923
Manager Char.										
Age (day)	1,487	16690	2690	9600	26124	826	17147	2455	11525	26063
Exp. (game)	1,686	228	241	1	1379	828	280	232	2	1312
Eng. Exp. (game)	1,686	208	229	1	1344	828	263	224	2	1312
Foreigner	1,499	0.048	0.214	0	1	828	0.027	0.161	0	1
Market Entry										
Player-manager	1,496	0.329	0.470	0	1	828	0.359	0.480	0	1
Other man. exp.	1,495	0.522	0.500	0	1	828	0.504	0.500	0	1
Intern hire	1,495	0.328	0.470	0	1	828	0.292	0.455	0	1
Playing history										
Play prof.	1,498	0.957	0.204	0	1	828	0.963	0.190	0	1
Play big 4	1,498	0.688	0.463	0	1	828	0.717	0.451	0	1
Num. Eng. Team	1,686	3.368	2.501	0	10	828	3.876	2.250	0	10
Ex-player club	1,686	0.319	0.466	0	1	828	0.225	0.418	0	1
International	1,498	0.395	0.489	0	1	828	0.412	0.492	0	1
Division	**Obs.**	**%Total**				**Obs.**	**%Total**			
1^{st}	300	17.79				152	18.4			
2^{nd}	466	27.64				251	30.3			
3^{rd}	446	26.45				203	24.5			
4^{th}	474	28.11				222	26.8			

Table 4: Count of 'mediocre' rehired managers by quality measure and division

Quality Estimate	Entry measure	Sample	Total Entrants	Av. # Entrants in Comp.	Rehires	Mediocre	% Mediocre
Spell FE	Median 5 year	Full	701	96	756	188	24.9%
		1st div.	79	97	143	21	14.7%
		2nd div.	175	96	235	44	18.7%
		3rd div.	199	96	180	54	30.0%
		4th div.	248	96	198	69	34.8%
	Median 5 year in div.	Full	701	26	695	189	27.2%
		1st div.	79	21	123	28	22.8%
		2nd div.	175	27	214	52	24.3%
		3rd div.	199	27	170	50	29.4%
		4th div.	248	27	188	59	31.4%
FE	Median 5 year	Full	701	96	756	220	29.1%
		1st div.	79	97	143	26	18.2%
		2nd div.	175	96	235	56	23.8%
		3rd div.	199	96	181	63	34.8%
		4th div.	248	96	197	75	38.1%
	Median 5 year in div.	Full	701	26	696	207	29.7%
		1st div.	79	21	123	31	25.2%
		2nd div.	175	27	215	49	22.8%
		3rd div.	199	27	170	57	33.5%
		4th div.	248	27	188	70	37.2%
Add win%	Median 5 year	Full	701	101	818	202	24.7%
		1st div.	79	102	150	32	21.3%
		2nd div.	175	102	250	51	20.4%
		3rd div.	199	101	202	57	28.2%
		4th div.	248	101	216	62	28.7%
	Median 5 year in div.	Full	701	28	755	198	26.2%
		1st div.	79	22	129	26	20.2%
		2nd div.	175	28	229	49	21.4%
		3rd div.	199	29	190	62	32.6%
		4th div.	248	30	207	61	29.5%

Table 5: Transition probabilities from 'mediocre' to 'good' manager over duration of employment spell

Quality Measure	Sample	End of Spell	Start of Spell: Mediocre		Start of Spell: Good	
Spell FE	Full	Total	188		568	
		Mediocre	125	66%	52	9%
		Good	63	34%	516	91%
	Per division	Total	174		470	
		Mediocre	115	66%	66	14%
		Good	59	34%	404	86%
FE	Full	Total	220		536	
		Mediocre	158	72%	33	6%
		Good	62	28%	503	94%
	Per division	Total	195		450	
		Mediocre	138	71%	39	9%
		Good	57	29%	411	91%
Add win %	Full	Total	202		616	
		Mediocre	144	71%	39	6%
		Good	58	29%	577	94%
	Per division	Total	188		513	
		Mediocre	133	71%	54	11%
		Good	55	29%	459	89%

Table 6: LPM results for probability that rehired manager is 'mediocre'

Quality Measure	Mediocre Rehire Median 5 Year Spell FE					
Learning measures						
Log games	-0.121***			-0.109***	-0.112***	-0.109***
	(0.013)			(0.015)	(0.015)	(0.015)
Log non-Eng. games	0.022**	0.006		0.035***	0.033***	0.037***
	(0.010)	(0.010)		(0.011)	(0.011)	(0.011)
Log obs.		-0.125***				
		(0.011)				
Exp. bins:						
< 20 games			-			
20-40 games			-0.237**			
			(0.094)			
40-80 games			-0.257***			
			(0.081)			
80+ games			-0.447***			
			(0.067)			
Manager Char.						
Log Age				-0.195	-0.184	-0.230*
				(0.127)	(0.134)	(0.132)
Foreign				-0.227**	-0.234**	-0.230**
				(0.091)	(0.092)	(0.093)
Time + Division						
Log Period				-0.034	-0.037	-0.017
				(0.045)	(0.046)	(0.046)
1st division				-	-	-
2nd division				0.019	0.021	0.017
				(0.044)	(0.044)	(0.044)
3rd division				0.133***	0.133***	0.133***
				(0.047)	(0.047)	(0.048)
4th division				0.165***	0.166***	0.156***
				(0.046)	(0.046)	(0.047)
Constant	0.869***	0.834***	0.643***	2.818**	2.708**	3.020**
	(0.069)	(0.056)	(0.064)	(1.153)	(1.221)	(1.210)
Entry mode	No	No	No	No	Yes	No
Playing career	No	No	No	No	No	Yes
Month FE	No	No	No	Yes	Yes	Yes
Obs.	756	756	756	756	756	756
R-sq.	0.102	0.136	0.074	0.142	0.145	0.150

Table 7: Probit results for labor market re-entry after employment spell ending

Rehired	(1) Spell FE	(2) FE	(3) Add Win %	(4)	(5)	(6) Spell FE	(7)
Quality Estimate	0.220***	0.262***	0.079***	0.164***	0.218***	0.241***	0.236***
	(0.043)	(0.045)	(0.014)	(0.052)	(0.065)	(0.067)	(0.071)
Average win%				0.016	-0.004	-0.011	-0.014
				(0.034)	(0.057)	(0.042)	(0.060)
Average goals pro				0.037	0.121**	0.137***	0.141**
				(0.029)	(0.051)	(0.040)	(0.060)
Number Games					0.179***	0.184***	0.188***
					(0.036)	(0.039)	(0.046)
Age					-1.793***	-1.967***	-2.005***
					(0.289)	(0.257)	(0.389)
Foreigner					1.076***	1.027***	0.566
					(0.331)	(0.327)	(0.403)
End period					0.505***	0.516***	0.479***
					(0.110)	(0.121)	(0.124)
Entry mode	No	No	No	No	No	Yes	No
Playing career	No	No	No	No	No	No	Yes
Month FE	No	No	No	No	Yes	Yes	Yes
Observations	1,384	1,384	1,590	1,384	1,251	1,249	1,249
Pseudo-R2	0.017	0.022	0.012	0.020	0.100	0.109	0.115
Log Likelihood	-813.8	-809.6	-953.0	-811.5	-699.6	-691.0	-686.3

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: Ordered probit results for career progression after employment spell ending

Career Progress	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Spell FE	FE	Add Win %		Spell FE		
Quality Estimate	0.175***	0.217***	0.081***	0.116***	0.131***	0.143***	0.140***
	(0.027)	(0.036)	(0.011)	(0.040)	(0.049)	(0.055)	(0.050)
Average win%				0.020	-0.010	-0.014	-0.015
				(0.021)	(0.033)	(0.029)	(0.035)
Average goals pro				0.033**	0.105***	0.114***	0.120***
				(0.016)	(0.036)	(0.037)	(0.034)
Number Games					0.150***	0.149***	0.146***
					(0.030)	(0.023)	(0.032)
Age					-1.475***	-1.555***	-1.707***
					(0.259)	(0.207)	(0.287)
Foreigner					0.447***	0.402***	0.171
					(0.118)	(0.102)	(0.159)
End period					0.389***	0.396***	0.360***
					(0.098)	(0.086)	(0.093)
Entry mode	No	No	No	No	No	Yes	No
Playing career	No	No	No	No	No	No	Yes
Month FE	No	No	No	No	Yes	Yes	Yes
Observations	1,384	1,384	1,590	1,384	1,251	1,249	1,249
Pseudo-R2	0.00742	0.0101	0.00884	0.00946	0.0410	0.0429	0.0466
Log Likelihood	-1839	-1834	-2104	-1836	-1612	-1607	-1601

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

9 Appendix tables

Table 9: Presence of mediocre rehires, alternative entrant quality measures

Quality Estimate	Entry measure	Sample	Av. # Entrants in Comp.	Rehires	Mediocre	% Mediocre
Spell FE	Average 5 year	Full	96	757	184	24.3%
		1st div.	97	143	19	13.3%
		2nd div.	96	235	46	19.6%
		3rd div.	96	181	55	30.4%
		4th div.	96	198	64	32.3%
	Average 5 year in div.	Full	26	699	185	26.5%
		1st div.	21	123	26	21.1%
		2nd div.	27	217	55	25.3%
		3rd div.	27	170	52	30.6%
		4th div.	27	189	52	27.5%
	Median 10 year	Full	202	757	201	26.6%
		1st div.	202	143	23	16.1%
		2nd div.	202	235	50	21.3%
		3rd div.	201	181	55	30.4%
		4th div.	202	198	73	36.9%
	Median 10 year in div.	Full	55	696	190	27.3%
		1st div.	44	123	26	21.1%
		2nd div.	55	216	53	24.5%
		3rd div.	58	170	51	30.0%
		4th div.	59	187	60	32.1%