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BETTER THE DEVIL YOU KNOW: MANAGERS' NETWORKS AND THEIR INFLUENCE ON HIRING, RESPONSIBILITIES, AND PERFORMANCE

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Better the Devil You Know: Managers' Networks and Their Influence on Hiring, Responsibilities, and Performance*

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Abstract

This paper investigates how managers leverage their professional networks (former employees) to influence three key dimensions: hiring, responsibilities, and performance. We use rich transactional data in professional football (soccer) in Europe: over 6k coaches, 80k players, and 100k movements. First, we find that managers rely heavily on their networks for hiring, particularly for non-star workers, and at a somewhat lower cost. Second, managers give network-hired workers more responsibilities, particularly in the first year. Third, network-recruited workers are significantly positively associated with performance. We conduct additional heterogeneity analyses and robustness tests, and discuss generalizability and implications for managers in other industries.

Keywords: managers, network, hiring, responsibilities, performance, football

JEL Classification: L14, J53, M51

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1 Introduction

Human capital and talent acquisition are essential for firm performance (Colbert, 2004). Employees carry substantial knowledge, skills, and expertise that can translate into a competitive advantage (Michaels et al., 2001). Among the strategies firms follow to improve human capital (Lepak and Snell, 1999), the external acquisition of talent, i.e., hiring employees who can immediately contribute, is beneficial because it allows for rapid productivity gains (Becker, 1964; Munyon et al., 2011). Employee mobility can improve organizational outcomes as new employees can deliver performance, build and adapt routines and systems, and create knowledge spillovers (Campbell et al., 2012; Mawdsley and Somaya, 2016).

Hiring the right workers is, however, a challenging task for firms, as they might not be able to accurately predict the contribution of potential employees (Chadwick and Dabu, 2009; Hoffman et al., 2018; Bertheau et al., 2026; Li et al., 2026). For example, productive workers can encounter barriers upon moving to new environments and firms, failing to adapt and replicate their previous performance (Dokko et al., 2009; Raffiee and Byun, 2020). Organizations must trust the new individual will create value, and the individual must expect a higher utility from the new job. How firms deal with this information asymmetry and uncertainty problem has attracted much research attention (Paul and Scott, 2011; Raffiee and Byun, 2020; Casoria et al., 2022; Brymer et al., 2024).

Previous research has demonstrated that the social ties of current employees play a key role in organizational hiring decisions (Rubineau and Fernandez, 2015) because they can reduce uncertainty and search frictions for new employees (Montgomery, 1991; Granovetter, 2018). Organizations are more likely to hire individuals with whom their members share characteristics, such as education (i.e., graduating from the same higher education institution, Rider (2012); Kacperczyk (2013); Hadlock and Pierce (2021); Carnahan et al. (2022)), professional background (i.e., working for the same institution, Brandes et al. (2015); Hensvik and Skans (2016); Cai et al. (2022); Hacamo and Kleiner (2022)), or ethnicity (i.e., having a shared cultural or ethnic background, Giuliano and Ransom (2013); Åslund et al. (2014); Kerr and Kerr (2021)).

However, shared characteristics do not fully capture the complexity of managers' social networks and their influence on hiring. While shared characteristics can be used to infer employee quality, we expect managers to have much more information about their former direct employees.

Managers who have directly supervised employees have insights into work ethic, reliability, teamwork, manageability, or fit within a proposed management style. This type of knowledge, gained through direct collaboration, is difficult for labor markets to price accurately and occurs across many professional contexts in which managers directly supervise and evaluate workers within teams.

To the best of our knowledge, no paper has systematically examined how managers use their own direct professional networks to acquire talent and determine individual and organizational outcomes—in large part because having high-quality data on management structure is hard to come by. Research faces limitations in quantifying the input of new employees hired from the manager's network and their influence on performance (Barwick et al., 2023). To test for the effects of hires from the direct network of managers, one, therefore, needs not only to be able to observe movements between firms but also to have some information about the firm structure (to be certain that a worker has worked with a manager before) and comparable performance metrics. These conditions are not easily satisfied in most labor market data; one usually has to make a trade-off between these conditions: either one studies a complete industry, where direct relationships might be unobserved (Rider, 2012; Hensvik and Skans, 2016), or one has access to detailed information for one firm but often at the expense of comparable performance metrics or observable movements across firms (Flory et al., 2015; Chen et al., 2020).

Two papers make progress on this front using large-scale administrative data: Fenizia (2022) covers office-employee data from the National Institute for Social Security in Italy, and Minni (2026) uses personnel records for tens of thousands of white-collar workers and managers across 100 countries. Both papers examine manager rotation and focus on how it shapes job allocation and worker outcomes within the firm. We focus on how managers leverage their personal networks to hire from outside the firm and examine the responsibilities given to the new hires, and their influence on team performance. In this line, Brandes et al. (2015) also analyze the performance effects of social tie hiring in the NBA using shared former employer as a proxy for social ties between managers and players. Shared employment at a given organization does not guarantee, however, that a manager and an employee have ever worked together directly, making it difficult to isolate the effect of personal knowledge acquired through direct supervision. This is precisely the mechanism our setting allows us to identify.

In this paper, we leverage the availability of large granular datasets from European football (soccer) to test for the effects of managers' networks on hiring, responsibilities given to workers, and firm performance. Our data covers both men's and women's professional football. We use data from the reference website on football transfers and performance, Transfermarkt, and its subsidiary Soccerdonna. This setting grants us access to the complete career and network records of thousands of managers and employees globally and to standardize the performance metrics of hundreds of firms over time. In total, our dataset covers a network of approximately 6,200 coaches, 83,000 players, 100,000 transfers, and 2,300 teams over 17 years.[1] This data satisfies all the conditions to investigate the role of managers' networks on hiring and performance, as we can observe complete networks in comparable international markets with high-stakes and standardized performance metrics. While European football is a very specific industry, it does provide several compelling methodological advantages and access to rich publicly available data. We believe this justifies looking at this particular corner of the world to study the links between managers' networks, hiring decisions, and firm performance, passing the "external validity-novelty" Litmus test (List, 2020, p. 45).

We consider an employee (player) to be in a manager's (coach's) network if the employee has previously worked for this specific manager. This tie involves daily interactions and implies a hierarchical "vertical" relationship (Ertug et al., 2020). Our definition of social tie maximizes managers' knowledge about potential employees: in football, we can be certain that a coach has worked directly with a player if they were employed by the same club at the same time, given that each club only has one (professional) team. This is a distinct advantage of our setting, as such certainty is harder to achieve in other industries with large multinational companies, where shared employment does not always imply direct collaboration. Additionally, we explore whether tie recency is relevant, as older connections may exist in a formal sense but carry less informational value (Granovetter, 1983). Our data allows us to examine three dimensions: the potential mechanisms that facilitate new hires, the responsibilities granted to network-recruited employees relative to those hired outside the network, and the effect of network hiring on team performance.[2]

[1]For men, the top 10 European leagues are considered; however, for women, all available data is taken into account to obtain a sufficient sample size.

[2]There are many instances of managers' new teams recruiting their former players in our database, meaning that we are statistically able to measure effects. The effectiveness of such practices on the team's performance is also debated in specialized press.

First, we examine how often managers use their network to hire new employees, considering both the cost of recruitment and the quality of employees. We expect that managers' insights and past experience with employees in their network will allow them to identify the best matches and facilitate the transfers. We find that managers are 12 times more likely to hire through their networks than random chance would predict, while attracting talent at lower costs (relative to their market valuation). Additionally, we can assess whether managers use their network to hire "star" or "second-tier" employees (Groysberg et al., 2008; Teece, 2003; Carnahan et al., 2012). We find that players recruited through the managers' networks have lower market values at the time of hire compared to players hired outside their network. This suggests that managers use their networks more for "second-tier" players, whose potential the market may undervalue or who would be a perfect fit to the manager's plan for the team.

Second, we consider how much managers trust the employees hired from their own network (Levin and Cross, 2004). Managers can use these marquee employees to transmit ideas, implement processes, and consolidate practices (Campbell et al., 2012; Mawdsley and Somaya, 2016). However, previous research lacks objective measures to quantify how much and how long managers rely on new employees (Mawdsley and Somaya, 2016). In this study, we examine whether managers grant employees hired from their network more responsibilities, relative to other team members. To measure this, we use the number of minutes played and games featured in the team. We also evaluate the managers' tenure at the firm as a moderating factor to analyze time dynamics. We find that, compared to players hired outside their network, network-recruited employees enjoy more responsibility in their first season with the team. This initial effect, however, vanishes (and even becomes negative) over time. This suggests that managers rely more on network hires during periods of organizational transition, when implementing new projects, and this dependence diminishes once the manager's project is established.

Third, we analyze how the number of employees recruited from the managers' network influences firm performance. The question of the effects of network-recruited employees has attracted much attention in the social network literature (Eliason et al., 2017; Burks et al., 2015; Barwick et al., 2023). We find that having more network-recruited players is associated with better firm performance, measured through the number of points and end-of-season rankings (although the marginal returns of a network-recruited player are decreasing). This is consistent with a smoother transition of workers under a newly-recruited manager.

This paper contributes to several strands of the literature. First, the paper contributes to the literature on how referrals and the social connections of incumbent employees affect new hires and their labor conditions, mostly using employer-employee and survey data (see, for example, Cingano and Rosolia (2012) in Italy, Kramarz and Skans (2014) in Sweden, Dustmann et al. (2016) and Glitz (2017) in Germany, Brown et al. (2016) and Schmutte (2015) in the United States, and Saygin et al. (2021) in Austria). Barwick et al. (2023) used novel geocoded phone records in China to show that referral jobs are associated with several quality measures. Generally, these papers show that coworker networks help recruit other high-quality employees who benefit from better labor conditions such as higher wages, increased probability of moving from a part-time to a full-time job, or shorter commutes. These studies predominantly examine horizontal peer relationships among coworkers. Our paper focuses, however, on the under-examined network of managers with influence on hiring decisions and responsibility for performance. Recent theoretical work by Bolte et al. (2025) highlights that referrals may affect worker conditions, e.g., tenure, though they note this dimension requires further empirical exploration. We advance knowledge on whether (and when) managers use these direct networks to acquire talent, the characteristics of the workers they recruit, and the responsibilities assigned to network hires within the new organization over time.

Second, this paper contributes to the literature on how hiring from social networks influences firm performance. Empirical studies in this area are scarce because comprehensive data on the performance of employees and employers is often unavailable (Barwick et al., 2023), but when such data exists, they typically focus on coworkers' networks and report a positive effect (see, for example, Eliason et al. (2017) in Sweden, Burks et al. (2015) in the US, and Barwick et al. (2023) in China). Although hiring through ties and referrals can improve firm performance by improving coordination, facilitating cooperation, and/or reducing information asymmetry, the management and organization literature also anticipates a detrimental effect linked to nepotism and lack of diversity (Beaman and Magruder, 2012; Brandes et al., 2015; Beaman et al., 2018; Ertug et al., 2020). Prior work, therefore, focuses on coworker networks or employee referrals more broadly, and the effects of managers' own networks on firm performance remain under-examined. We contribute by examining how manager network hires specifically affect firm performance using comparable, standardized performance metrics across firms and countries. We additionally observe manager-employee pairs over time as they move between organizations, a data advantage rarely available in the literature. We find a positive effect of hiring through managers' networks on firm performance, but with decreasing marginal returns of each additional network hire.

Third, this paper contributes to the literature on how firms deal with hiring frictions on the labor market and on network spillovers of managers. While frictions have mostly been studied on the supply-side -e.g., reducing job seekers' search costs, upskilling and or facilitating signaling to employers (Alfonsi et al., 2022; Bassi and Nansamba, 2022; Caria et al., 2024)-, a recent, smaller branch of literature has investigated the role of demand-side barriers to labor market matching frictions (Bidwell et al., 2023; Lallemant, 2025), particularly around reducing information frictions (Abebe et al., 2021; Fernando et al., 2023). This paper contributes to this literature by investigating the role of a prominent strategy used by employers to reduce uncertainty: hiring through networks. One channel through which this strategy operates is the spillover of managers' professional networks across organizations. For instance, the literature has highlighted that recruiting managers can increase access to the new employee's former firm's clients (Rogan, 2014; Briscoe and Rogan, 2016; Mion et al., 2016; Patault and Lenoir, 2024). While these studies examine client spillovers or manager-worker complementarities, we focus on a different type of spillover: managers' ability to leverage their professional networks to acquire talent. Several papers have also shown the benefits of good vertical relations between managers and workers to influence firm outcomes (Lazear et al., 2015; Peeters et al., 2020; Hoffman and Tadelis, 2021). Building on this literature, we analyze whether managers may attract their former employees at a lower acquisition cost (based on market valuation) than other workers, demonstrating how the vertical relationships established between managers and employees may create value for organizations. We rely on a multi-country analysis with firms competing for talent in a global market.

Finally, this paper adds to the literature using "sports as a lab" (Kahn, 2000). Previous research has used sports data because it offers objective performance measures from public sources that allow the testing of economic and managerial theories (Day et al., 2012; Fonti et al., 2023; Glennon et al., 2025; Ahmadi et al., 2025; Gomez-Gonzalez et al., 2025). In this paper, we specifically add to the literature that examines how managers impact firm strategy and performance (Brandes et al., 2015; Peeters et al., 2020), and the influence of networks in hiring (Velema, 2021). For instance, Dalton and Landry (2020) show that NBA employers over-weight first-hand experience in hiring decisions, favoring players who performed unusually well when facing the employer's team; a distinct mechanism from the sustained supervisory knowledge we study here. Peeters et al. (2020) show that matching middle and upper managers and their level of cooperation is a significant driver of firm performance using panel data from the US Major League Baseball. Closely related to our paper, Brandes et al. (2015) show that teams with general managers who recruit players from their former employer in the US National Basketball Association tend to perform worse. However, their focus on institutional ties (shared former employer) does not identify whether managers had direct supervisory relationships with recruited players. In this paper, we leverage a large dataset on firm performance and inter-organizational mobility (including transfers, fees, and contract duration) from professional football to contribute to two key dimensions. First, we study the direct network of managers (head coaches) rather than institutional ties, thereby isolating the role of personal knowledge gained through direct supervision. Second, we link this tight working relationship between head coaches and players to hiring decisions, allocation of responsibilities, and firm performance. Moreover, our analysis includes data from both men's and women's football settings, enabling us to assess whether manager network hiring patterns are consistent across contexts. This inclusion is relevant as women's professional sports data are rarely examined in labor economics research.[3]

We discuss the extent to which our findings can be generalized to other industries and markets. In the institutional background and discussion sections, we highlight the similarities and differences between the roles and tasks of managers and players in football clubs and managers and workers in other industries. In the discussion section, we discuss differences between our studied market and other industries in terms of beliefs about the transferability of skills across firms and incentives faced by managers and firms.

The remainder of the paper is structured as follows. Section 2 offers details about the institutional background. Section 3 presents the data used in the paper and Section 4 details the empirical strategy. Section 5 presents the results and Section 6 discusses the findings and concludes.

[3]Men's and women's leagues are at different development stages, which significantly influences particular outcomes such as transfer fees. Rather than directly comparing the magnitude of some men's and women's outcomes, we examine whether similar networking and hiring patterns exist in both markets.

2 Institutional Background

2.1 European football labor context

Substantial granular data on inter-organizational mobility is essential to evaluate the effects of managers' networks on hiring and performance. Tracking workers when they change firms over time is very difficult in most labor markets. Even when such tracking is feasible, obtaining proper information about individual productivity and firm structure is often impossible, e.g., which workers work with which managers and in which specific tasks (Fahrenkopf et al., 2020).

In this sense, European football offers an ideal setting for multiple reasons. First, the market is large and economically significant, with growing European league revenues now reaching as high as €30 billion annually (Deloitte, 2023). European football also attracts talent globally, with thousands of workers moving from more than 150 different countries every year (Glennon et al., 2025). Second, and particularly relevant for our purpose, is that the tasks employees (players) and managers (coaches) engage in are very similar across teams (Dietl et al., 2011; Pieper et al., 2014; Gomez-Gonzalez et al., 2019). This allows for the comparison across time, teams, and countries. Third, professional sports offer a lot of publicly available data to test for economic and management theories (see Fonti et al. (2023) for a review). Here, we briefly introduce how football is organized in Europe.

Club football in Europe is organized as follows. National federations organize leagues, which are year-long competitions where every team competes against all others, usually twice a year (once in their home stadium, once in the opponent's stadium). The structure of leagues is very similar across countries. Within countries, teams compete in a promotion and relegation system, where successful clubs in lower divisions (ex: France's *Ligue 2* or Germany's *2. Bundesliga*) can move up to higher leagues (*Ligue 1* or *1. Bundesliga*). In contrast, poorly performing teams face relegation.[4] In European football, some teams can also compete against teams from leagues in other European countries in competitions that take place every year. In this paper, we focus solely on national leagues and not on other competitions, such as domestic cups or European leagues, because of lower comparability.

Each team in the league is composed of players and coaching staff headed by a head coach

[4]This is different from major leagues in the US, where teams are guaranteed to compete in the same league yearly.

(whose role is detailed in the next paragraphs). Outside of transfer windows, where teams are allowed to trade players (more on this below), squads of players are stable. As opposed to firms in other industries, European football teams (with some exceptions) do not aim to maximize profits but rather revenues so they can afford new talent investments (Késenne, 2000; Garcia-del Barrio and Szymanski, 2009). We refer to the generalizability of our findings in the discussion.

2.2 Managerial tasks of coaches

In football, coaches act as managers of their team of players. Coaches are responsible for the team's day-to-day activities, including organizing training sessions, preparing game strategies, selecting the squad to play in games, and making on-field decisions such as tactics and player substitutions. In their task, coaches can be assisted, especially in big professional teams, by their assistants, who might be responsible only for specific tasks (e.g., fitness coach, second coach, goalkeeper coach, coach for set-pieces). When landing at a new team, coaches usually bring their assistants. Coaches also serve as the team's public face, acting as a link between players and other stakeholders, including owners, media, and fans. They rank among the highest-paid team employees, with top teams regularly paying their coaches millions of euros annually.[5]

Head coaches also have substantial power over hiring decisions. For example, they decide whether and, if so, under what conditions the team signs a new player, renews a player's contract, or transfers a player to another club. As such, players face the same types of incentives as employees in other industries, in that they need to perform their tasks well and impress their manager (Muehlheusser et al., 2018). Coaches, therefore, have a strong hand in shaping the structure of the team, and successful coaches, like successful managers, can help shape industry standards (e.g., Ralf Rangnick, a German coach and the inventor of "gegenpressing", a tactic in which teams try to immediately win back possession after losing the ball, or Pep Guardiola, a Spanish coach and the architect of "tiki-taka", a tactic in which teams keep ball possession with short and accurate passes).

[5] See for instance https://frontofficesports.com/highest-paid-soccer-managers/.

2.3 Employee mobility (transfers) in European football

In most instances, the European football market operates like any other market in the corporate setting (with some exceptions as described by Glennon et al. (2025)). The mobility of players is key to our research. In football, a player's movement between teams is called a transfer. Like in other industries, there are almost no restrictions regarding the salary and contract duration that players negotiate with teams.[6] The three main differences in inter-organizational mobility between European football and other industries are as follows.

First, if the player is still under contract with the former team, the new team pays a transfer fee to compensate for the loss of the worker.[7] The fee can vary depending on many factors, such as skills, age, position, or current contract (Franceschi et al., 2024). Once a player has decided to join a new team, both the player and the current employer have a strong incentive to negotiate the exit. If the player reaches the end of the contract, the new team can simply recruit the player for free (called a "free transfer"). Another transaction option between clubs is to loan players (with or without a loan fee), where the borrowing team pays (part of) the player's salary. Second, the transfers can only happen during specific periods known as transfer windows, which are set times when clubs are allowed to buy, sell, or loan players.[8] Third, players have agents who negotiate the transfer conditions, salary, and contract duration.

The football transfer market provides rich transactional data, including transfers, fees, and contract durations of highly skilled workers. Unfortunately, we cannot access salary data, which is restricted and opaque for long time series. The European transfer market represented approximately €12 billion in 2023 (CIES Football Observatory, 2024). In our dataset, the average transfer fee is around €1,240,000 for men and €790 for women, and no fee was paid for most transfers.[9] The highest transfer fee registered was €222,000,000 in 2017 when Paris Saint-German (France) hired the player Neymar from FC Barcelona (Spain). The next section provides more detailed

[6] This is a substantial difference with major sports leagues in the US, where salary caps regulate individual wages and team bills. In Europe, only the set of rules implemented by UEFA under the Financial Fair Play umbrella in 2010 has attempted to limit clubs' spending in talent acquisition with some controversy and modest results (Peeters and Szymanski, 2014).

[7] This is a substantial difference from major US sports' trades, where teams typically exchange player contracts, with no transfer fee between teams.

[8] There are two transfer windows: one between seasons in summer and another mid-season in winter.

[9] The women's transfer market is still much smaller than the men's, with only very top teams paying transfer fees for star players. For example, only two transfers (out of more than 200) were known to involve a fee in the 2024 summer transfer window for the English Women's Super League (Sky Sports, 2024).

information on our dataset.

3 Data

In this paper, we use transfer and performance data in European football to evaluate the effects of managers' networks. For men, we scraped data for 14 seasons—from 2008/2009 to 2021/2022—from the website Transfermarkt (see details below). For women, we collected the same data for the seasons 2019/2020 to 2024/2025 from the website Soccerdonna (data for previous years for women were too sparse). Descriptive statistics are presented in Table 1 for men and Table 2 for women. The choice of seasons was made for data availability reasons.

3.1 Data source

Our data comes from Transfermarkt[10] for men's leagues and its subsidiary Soccerdonna[11] for women's leagues. These websites centralize information about teams, coaches, players, performances, and transfers in all main football leagues worldwide. The websites collect transfer data for all top leagues and provide market value assessments for players, defined as the expected value of a player in a free market. While the exact formula to determine the market value of players is not fully transparent, we know community members make predictions based on players' characteristics, performances, and contractual relationships. The most important factors considered in the valuation include age, current performance at club and national team level, development potential, league level and financial conditions, reputation, marketing value, injury susceptibility, and contract length (Transfermarkt, 2026). Market values are updated at least twice per season (once at the end of the season and once mid-season) with additional interim updates for individual players experiencing notable changes in form or playing time (Transfermarkt, 2026). In our data, we use the market value recorded at the time of each transfer.

Crowd-based market value estimations may be somewhat biased as (for example) social influences can undermine the wisdom of the crowd effect (Lorenz et al., 2011). Market value is not intended as a direct prediction of the transfer fee. It represents an estimate of what a club

[10] https://www.transfermarkt.com/
[11] https://www.soccerdonna.com/

would be willing to pay to sign a player independent of whether an actual transaction occurs, incorporating both current performance and future potential (Müller et al., 2017). This explains why market value can exceed or be below the realized transfer fee. Importantly for our research, the crowd-based "market values" may incorporate some noise, but they are accurate, are highly correlated with actual transfer fees (Müller et al., 2017), and influence negotiations between clubs and players (Coates and Parshakov, 2022).

In European football, where player salaries are rarely publicly disclosed, the literature uses the market value from Transfermarkt as a proxy for player compensation given its high correlation (Prockl and Frick, 2018). Transfermarkt data have been extensively used to analyze labor market issues such as immigration and employee mobility (Glennon et al., 2025), firm valuation (Scelles et al., 2016), rewarding luck (Gauriot and Page, 2019), or predicting performance (Peeters, 2018).

3.2 Team data

For men, we scraped the information about all clubs who played at least one season in the first two divisions in the top 10 European leagues, according to the ranking by the Union of European Football Associations (UEFA).[12] The leagues are (in alphabetical order): Austria, Belgium, England, France, Germany, Italy, Netherlands, Portugal, Spain, and Scotland. For women, we used the entire data from Soccerdonna to obtain a sufficiently large number of observations. The sample consists of 570 men's teams and 1,781 women's teams.

For each team, we scraped the roster for each season and their history of coaches. We also collected their performance results (total number of points and end-of-season ranking).

3.3 Coach data

For every team in our sample, we scraped the entirety of their coaching history. After removing the coaches who never coached in the relevant period, we have a sample of 2,807 coaches for men and 3,411 for women.

For each coach, we collected their entire coaching history, as well as performance metrics of their tenure with each team (length of tenure, number of games played, points per game).

[12] Accessible here.

3.4 Player data

We scraped the team roster (all the players under contract) for each team in every season of our sample. We first scraped information about the players' demographics (nationality, birth year, position). We then scraped their performance history (minutes and games played in each season). Last, we scraped their transfer history, giving us the origin and destination team, the transfer fee, and the estimated market value at the time of the transfer.

The number of individual players in the final data is 38,402 men's players and 44,538 women's players, representing 201 and 163 different nationalities, respectively.[13] For men's players, we have approximately 90,000 transfers (~ 6.5k transfers per season), for which we have fee information for 50,000. For women's players, we have approximately 18,000 transfers, out of which only 110 transfers have a non-zero fee.[14]

3.5 Final data

For the analysis below, we need to evaluate the effects of managers' networks on three dimensions: hiring, responsibilities given, and team performance.

The first step in the analysis is to define what coach networks are. We define a player as being in a coach's network if the new team's coach had already coached the player in a previous season. For example, in August 2010, the player Ricardo Carvalho was transferred from Chelsea (England) to Real Madrid (Spain). The coach of Real Madrid at the time was José Mourinho, who was the previous coach of Carvalho in Porto (Portugal) in 2003/2004. The *Transfer from network* variable would therefore be coded as 1. As an example, all transfers with a fee above €1 million in the season 2021/2022 are displayed in Figure A, and aggregates of all transfers between the "Big five" leagues (England, France, Germany, Italy and Spain) are displayed in Figure A.2.

While our data is restricted to a few countries, we capture the complexity of competing clubs hiring globally and players engaging in several transfers during their careers. To define the *Transfer from network* variable, we use the entire player's career, not only the teams included in our final

[13] The top 5 nationalities for men's players are Italian, Spanish, French, English, and German, and the top 5 nationalities for women's players are German, Mexican, Spanish, Finnish, and Danish.

[14] The results for women on the cost-of-recruitment analysis should be interpreted cautiously given the lack of fee data.

dataset. We include player-coach links in our analysis regardless of when or where they were originally formed—whether they occurred in a different country/continent or outside of our studied time period. In our dataset, the percentage of transfers that occur within the manager's network is approximately 11% for men and 1% for women. As an alternative measure of network transfers, we construct the variable *Transfer from network* using time windows of 1, 3, and 5 years to account for tie recency. The respective time window indicates the maximum number of years before the transfer during which a prior player–coach connection qualifies the transfer as occurring within the network.

To determine if teams pay a premium when recruiting from a manager's network, we calculated how much each transfer fee differed from the player's market value at the time of the transfer. A positive value means the team paid a premium for recruiting a given player. For both men and women, we find that the average of this difference is negative, meaning that teams typically pay fees lower than the market values for players. This is likely because many transfers occur at the end of the player's contract, where the destination team does not need to pay money to the origin team.

Descriptive statistics are displayed in Table 1 for men and Table 2 for women.

4 Estimation Strategy

We examine managers' networks' effects on hiring, responsibilities given to employees, and firm performance. In what follows, we use the subscript i to refer to the individual players, t to refer to transfers, s to refer to seasons (i.e., year) and d for destination team.

Hiring. We look at two different dimensions of hiring: the quality of employees and the costs of recruitment. For the quality of employee recruited, we estimate the following equation, for player i, at the level of the transfer t to team d, in season s:[15]

$$\text{log(Market value+1)}_{t,i,d,s} = \alpha_0 + \alpha_1 \text{ Transfer from network}_{t,i,d,s} + \alpha_2 \text{ X}_{i,s} + \alpha_d + \alpha_s + \epsilon^1_{t,i,d,s} \quad (1)$$

[15]For all our models, we use robust standard errors clustered at the team level.

Table 1: Descriptive statistics, men's data

Variable	N	Mean	Std. Dev.	Min	Q1	Q2	Q3	Max
Panel A: Teams								
Points	6673	50	16	0	39	49	61	106
Rank	6673	-9.3	5.8	-24	-14	-9	-4	-1
Coaches per season	7276	1.3	0.57	1	1	1	1	5
Players per season	7276	26	7.9	1	23	28	31	55
Panel B: Coaches								
Nb teams coached	3005	2.2	1.9	1	1	1	3	13
Tenure length (days)	6725	468	1217	0	145	282	553	44,941
Nb games	6722	47	52	1	15	30	60	681
Nb players total	3005	67	64	1	25	38	91	385
Panel C: Players								
Birth year	39,304	1991	7.2	1960	1986	1991	1996	2006
Nb teams in career	39,385	2.5	1.8	1	1	2	3	15
Minutes played	190,311	1,834	1,553	1	458	1,530	2,859	9,215
Games played	190,311	26	20	1	9	24	38	117
Panel D: Transfers								
Avg. market value	106,288	2,138	5,805	0	225	500	1,500	180,000
Market value (transfer)	77,335	1,471	3,918	10	200	400	1,000	150,000
Transfer fee	44,785	1,206	4959	0	0	0	250	222,000
Fee - Market value	38,627	-535	3,196	-81,500	-700	-300	-100	122,000
Panel E: Player - coach relation								
Transfer from network	95,063	0.11	0.31	0	0	0	0	1
Transfer from network (1 year window)	95,063	0.067	0.25	0	0	0	0	1
Transfer from network (3 year window)	95,063	0.089	0.28	0	0	0	0	1
Transfer from network (5 year window)	95,063	0.098	0.3	0	0	0	0	1
Social tie	190,311	0.065	0.25	0	0	0	0	1

Note: Q1, Q2, and Q3 represent quartiles. The *Rank* variable is the opposite of the rank of the team at the end of the season (a higher value of the variable corresponds to better results). The variable *Transfer from network* is a dummy equal to 1 if, at the time of a transfer, the player had already been coached by the coach of his new team. The *Transfer from network (X year window)* variable restricts the link between the coach and the player to X years. The *Social tie* variable is similar but equals to 1 only if the coach coached the player before and the coach transferred the player to the team. Market values and transfer fees values are displayed in thousands of euros.

Table 2: Descriptive statistics, women's data

Variable	N	Mean	Std. Dev.	Min	Q1	Q2	Q3	Max
Panel A: Teams								
Points	2,228	25	15	0	13	23	35	90
Rank	2,228	-6.4	3.7	-19	-9	-6	-3	-1
Coaches per season	2,613	1.2	0.51	1	1	1	1	5
Players per season	2,613	7	5.1	1	3	6	10	31
Panel B: Coaches								
Nb teams coached	2,784	1.2	0.43	1	1	1	1	4
Tenure length (days)	3211	371	401	0	70	245	539	1939
Panel C: Players								
Birth year	12,662	1999	4.9	1970	1996	2000	2003	2009
Nb teams in career	13,669	1.3	0.62	1	1	1	1	6
Minutes played	18,379	885	713	0	245	750	1392	3665
Games played	18,379	13	8.9	0	5	12	20	47
Panel D: Transfers								
Avg. market value	1,691	30	33	0	10	20	35	300
Market value (transfer)	1,620	27	27	0	14	20	30	300
Transfer fee	18,328	0.44	8.2	0	0	0	0	470
Fee - Market value	1,620	-24	31	-300	-30	-20	-12	273
Panel E: Player - coach relation								
Transfer from network	18,328	0.0085	0.092	0	0	0	0	1
Transfer from network (1 year window)	18,328	0.0064	0.08	0	0	0	0	1
Transfer from network (3 year window)	18,328	0.0081	0.09	0	0	0	0	1
Transfer from network (5 year window)	18,328	0.0083	0.091	0	0	0	0	1
Social tie	18,379	0.0084	0.091	0	0	0	0	1

Note: Q1, Q2, and Q3 represent quartiles. The *Rank* variable is the opposite of the rank of the team at the end of the season (a higher value of the variable corresponds to better results). The variable *Transfer from network* is a dummy equal to 1 if, at the time of a transfer, the player had already been coached by the coach of his new team. The *Transfer from network (X year window)* variable restricts the link between the coach and the player to X years. The *Social tie* variable is similar but equals to 1 only if the coach coached the player before and the coach transferred the player to the team. Market values and transfer fees values are displayed in thousands of euros.

where α_d and α_s represent team and season fixed effects. We also control for player i's age at the time of transfer, nationality, and position (vector denoted by $X_{i,s}$).[16] As an alternative measurement, we use the raw market value (without log).

The coefficient of interest in Equation 1 is α_1. $\alpha_1 > 0$ would mean that players recruited through the coach's network are more valuable, ceteris paribus. Put differently, it would indicate that managers use their network to attract "star" players. On the other hand, if $\alpha_1 < 0$, it means that managers use their network to recruit lower-quality players, i.e., "squad" players.

To evaluate the influence of managers' networks on the costs of recruiting, we then estimate the following equation, where the outcome variable, $\Delta_{t,i,d,s}$, is the difference between the transfer fee (what the firm pays) and the market value of the player:

$$\Delta_{t,i,d,s} = \beta_0 + \beta_1 \text{ Transfer from network}_{t,i,d,s} + \beta_2 \text{ X}_{i,s} + \beta_d + \beta_s + \epsilon^2_{t,i,d,s} \tag{2}$$

A positive β_1 would indicate that managers need to pay a premium to recruit players from their network, while a negative β_1 would indicate that they are able to attract players at a lower cost. In an alternative specification, we use the transfer fee as the outcome variable, controlling for the player's market value.

Responsibilities. We define responsibility in our context as the coach putting the player on the pitch for games. On average, men's teams have 26 players and women's teams 19 players in their roster, but can only play up to 16 players per game (11 starters and up to five substitutions), so having more game time proves that the coach gives a player more responsibilities. The two outcome variables that we will use are the number of minutes played and games played in a season. The unit of observation is player i-season s, where the player plays for team d. We control for player tenure at the club, as well as age at the time of the season, and other characteristics of the player and the team. We also control for season fixed effects. The estimated equation is, therefore, the following:

$$Y_{i,s,d} = \gamma_0 + \gamma_1 \text{ Social tie}_{i,s,d} + \gamma_2 \text{ Tenure}_{i,s,d} + \gamma_3 \text{ Social tie}_{i,s,d} \times \text{ Tenure}_{i,s,d} + \gamma_4 \text{ X}_{i,s} + \gamma_t + \gamma_s + \epsilon^3_{i,d,s} \tag{3}$$

[16]Note that because of data availability, we cannot control for position and average market value in models using women's data.

A positive γ_1 would indicate that players recruited through the manager's network are being given more responsibilities on average, while the interaction term (γ_3) indicates whether this bias in favor of "known" players is increasing or decreasing with tenure at the club.

Firm performance. The final dimension of analysis of the effects of managers' networks is on firm performance. Our two measures of performance are the total number of points at the season's end[17] and the final ranking in the league. To make coefficients comparable, we took the opposite of the final ranking as the outcome so that a positive coefficient is associated with a better ranking.

To evaluate the effect of players recruited through the managers' networks on performance, we calculated the number of players recruited by the manager's network for each team and season by counting the instances where *Transfer from Network* equaled 1. To control for nonlinearity, we also computed the square of this variable.[18] We then estimate the following equation, where the unit of analysis is team d-season s:

$$Y_{d,s} = \delta_0 + \delta_1 \text{ Nb players from network}_{d,s} + \delta_2 \text{ Nb players from network}^2_{d,s} + \delta_3 X_{d,s} + \delta_d + \delta_s + \epsilon^4_{d,s} \tag{4}$$

5 Results

Result 1: Transfers occur more frequently in the managers' networks than they would at random.

To test for the prevalence of recruitment within managers' networks, we compared the realized network distribution and the distribution expected under random networks. We start by evaluating this difference in men's data. On average, players work with approximately 5.1 distinct coaches over their careers. If transfers were completely random, the probability of joining a former coach in any of the 570 clubs in our sample would be about 0.9%. In contrast, we observe that 10.7% of transfers in our data are to clubs where a former coach is currently active-nearly than 12 times higher than under random networks. Given our sample of more than 95,000 transfers, the likelihood of observing such a large deviation by chance is effectively 0. Alternative definitions of

[17] In national leagues, a win earns a team three points, a draw one point, and a loss zero points.

[18] As a robustness check to control for teams that might be recruiting more in general, we perform the same regression with the share of players transferred within the network.

the random network, including restricting to within-country transfers and restricting the time window for the transfer to be within-network, yield very similar results (see Table B.1). The share of within-network transfer is higher in non-free transfers than free transfers, indicating that managers do not use their networks to better identify players that they can recruit for free.

Interestingly, this result is stronger for coaches from their second year of management of the team (the share of transfers occurring within network in the first year of the coach as head of the team is 6.3%, while in later years it is 20.3%). In the women's data, 0.8% of transfers occur within the coaches' network. Under random assignment, the baseline probability is 0.11%, based on an average of 1.73 coaches per career across 1,433 possible teams. This implies the observed rate is roughly 7 times higher than expected. Again, given our sample of more than 18,000 transfers, the likelihood of such a deviation occurring by chance is essentially 0.

Result 2: Managers tend to use their networks to recruit players of lower quality than other recruits.

Table 3: Hiring decisions

	Men		Women	
	Log Market value	Fee - Market value	Log Market value	Fee - Market value
	(1)	(2)	(3)	(4)
Transfer from network	-0.090^{***}	-101.487^{**}	0.274	-9.728
	(0.015)	(48.781)	(0.189)	(7.265)
Age	0.053^{***}	-99.330^{***}	0.046^{***}	-1.719^{***}
	(0.002)	(8.855)	(0.005)	(0.290)
Constant	4.472^{***}	$1{,}818.697^{***}$	1.724^{***}	27.108^{**}
	(0.254)	(253.604)	(0.234)	(13.180)
Position FE	✓	✓		
Nationality FE	✓	✓	✓	✓
Team FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	77,204	38,532	1,614	1,615
R^2	0.542	0.084	0.557	0.333

Note: The dependent variable in Columns 1 and 3 is the metric for quality of workers, represented by the market value of the player at the time of the transfer. In Columns 2 and 4, the dependent variable is the difference between what the team pays for the player and the market value. Both variables are coded in thousands of euros. The *Transfer from network* variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. *Nationality FE* captures the player's nationality. Robust standard errors clustered on the team level. * $p < 0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Column 1 of Table 3 displays the results of the estimation of Equation 1 on the quality of players. It appears that at the time of the transfer, players recruited through the coach's network have a lower market value than other recruited players. This means that managers use their networks not to recruit stars but rather to recruit squad players. The effect is relatively modest in terms of magnitude, with players recruited in the manager's network valued on average approximately 9 percent lower market value than players recruited outside it, corresponding to a 0.06 standard deviation lower valuation. As for Result 1, the effect is stronger for coaches after their first season (Table B.2, Column 1). For women's data (Column 3), possibly due to the much smaller sample size, the coefficient is not statistically significant. Results are stable by looking at the raw market value (Table B.3, Column 1 and 3). Restricting the time window for the transfer to be counted as within-network (Table B.4) indicates that the result is stronger for transfers where the link between the player and the manager is more recent (Column 1), further indicating that the mechanism could be better information. Interestingly, players recruited through the managers' networks are older and have played fewer minutes in the previous season (Table B.6). Table B.7 indicates that the result is actually reversed when considering only players for whom a positive transfer fee is paid. For women's data, players recruited through the managers' networks have played, however, more minutes in the previous season.

Result 3: Managers are able to attract players from their network at a lower price.

Column 2 of Table 3 indicates that players recruited through the manager's network are recruited at a lower price relative to their market value. As players recruited through the network have lower market values (previous result), teams can attract players inside the manager's network at an even lower cost. In terms of magnitude, being transferred from the manager's network is associated with a transfer fee of approximately €85k lower (net) of market value. This corresponds to approximately 0.02 standard deviation of market values. This result, contrary to the first two, is stronger for the first year of the manager in the club (Table B.2, Column 2). Table B.7 shows that the difference between transfer fee and market value is even stronger for transfers with a non-zero transfer fee. For women, the analysis does not yield significant results (Column 4), mainly because most transfers are free transfers in women's leagues.[19]

Result 4: Managers give more responsibilities to workers with whom they share a social tie at

[19] Table B.3 in the appendix presents the results for the log of the market value (log(Market value + 1), as many values in the women's dataset are zero) and transfer fee (controlling for the player's market value). Results are qualitatively similar, although the coefficient is no longer statistically significant for transfer fees.

the beginning of their tenure at the club and reduce this premium over time.

Table 4: Responsibilities

	Men		Women	
	Minutes played	Games played	Minutes played	Games played
	(1)	(2)	(3)	(4)
Social tie	98.694***	0.871**	161.032**	1.496**
	(25.930)	(0.345)	(68.632)	(0.740)
Tenure	72.107***	0.832***	−9.802	−0.464
	(3.895)	(0.046)	(48.566)	(0.524)
Social tie × Tenure	−189.373***	−2.362***	202.569	2.945**
	(19.501)	(0.250)	(125.621)	(1.410)
Constant	−5,412.114***	−49.733***	−1,546.518***	−13.707***
	(816.618)	(10.201)	(379.076)	(4.376)
Individual controls	✓	✓	✓	✓
Position FE	✓	✓		
Nationality FE	✓	✓	✓	✓
Team FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	106,045	106,045	17,277	17,277
R^2	0.128	0.125	0.277	0.352

Note: The dependent variable in Columns 1 and 3 is the number of minutes played over a season. In Columns 2 and 4, the dependent variable is the number of games played in a given season. The *Social tie* variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer, and remains a 1 for every season following the transfer. The *Tenure* variable represents the number of years the player has been playing for the club. *Nationality FE* captures the player nationalities and the nationality tie between the manager and the player. Individual controls include market value (only for men), age and age squared. Robust standard errors clustered at the team level. *p<0.1; **p<0.05; ***p<0.01.

Table 4 indicates that players recruited through the coach's network tend to be given more responsibilities, as measured by the number of games and minutes played. In the first year of the player in the team, players recruited through the coach's network play the equivalent of approximately one extra game in the season. This corresponds to approximately a 0.06 standard deviation increase. The interaction term with tenure at the club indicates that this effect fades rather quickly, as players recruited through the manager's network actually play fewer games and fewer minutes starting with their second season with the coach they are reunited with. Interestingly, the positive result for the first year of the player at the club holds regardless of whether the player was recruited during the manager's first season at the club, while the negative effect in later years is driven by players who were recruited by the manager in his later years at the club (Table B.8). Restricting the time window for the transfer to be counted as within-network (Tables B.9 and B.10) doesn't meaningfully change the results. The increased responsibilities are associated with an increase in players' market value (Table B.11).

Women's results are similar to men's for the first season (Columns 3 and 4), but the diminishing result with tenure at the club is not present. Players recruited through the manager's network also tend to play more minutes and games, with diminishing effects over time. The magnitude of the effects is slightly larger for women than men[20].

Result 5: The relationship between the number of players recruited through the manager's network and performance is an inverted U-shape, with positive but decreasing marginal returns.

Results from Table 5, Columns 1 and 2, indicate that an increase in the number of players recruited from the manager's network is associated with significantly higher performance for the team. In terms of magnitude, increasing the number of network-recruited players by one is associated with 0.88 points more at the end of the season (approx. 1/3 of a win) and a 0.34 position higher ranking. Interestingly, the coefficient for the squared term is negative and statistically significant, meaning there is a decreasing return to network-recruited players. Results are stable to the use of the share of network-recruited players instead of its number (Table B.12) and to the inclusion of the average team performance as control (average points and rank throughout the period, Table B.13).

Back-of-the-envelope calculations indicate that the peak of performance would be obtained for approximately seven players recruited through the manager's network. Given that, on average, a team has 1.89 players recruited from the manager's network, the returns would still be very positive. Data for women (Columns 3 and 4) show a different pattern, but the number of observations is much smaller and the results are insignificant.

6 Discussion and Conclusion

Hiring the right workers is essential for firm growth (Michaels et al., 2001; Colbert, 2004). Managers can play a crucial role in identifying talent, as their substantial information about former workers can reduce uncertainty about fit (Montgomery, 1991; Granovetter, 2018). In this paper,

[20]This makes sense because women's leagues typically have fewer teams and thus fewer games and fewer minutes per season.

Table 5: Firm Performance

	Men		Women	
	Total points	Rank	Total points	Rank
	(1)	(2)	(3)	(4)
Nb players from network	0.882***	0.343***	−2.985	−0.377
	(0.158)	(0.064)	(2.035)	(0.579)
Nb players from network sq	−0.064***	−0.024***	0.789*	0.092
	(0.019)	(0.008)	(0.417)	(0.108)
Constant	32.336***	−21.051***	64.019***	5.409
	(6.902)	(2.026)	(12.919)	(4.579)
Team FE	✓	✓	✓	✓
League FE	✓	✓	✓	✓
Division FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	6,424	6,424	2,228	2,228
R^2	0.579	0.480	0.811	0.823

Note: The dependent variable in Columns 1 and 3 is the number of points a team got in a season. In Columns 2 and 4, the dependent variable is the opposite of the rank, meaning that an increase in the dependent variable corresponds to a better rank. The variable *Recruited from network* is an integer representing the number of players in the squad who were recruited from the coach's network. We control for the average market value in the team. Robust standard errors clustered on the team level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

we leverage the public availability of data in the European football market to study how managers use their networks to impact three dimensions: hiring, responsibilities, and performance.

First, we find that managers rely substantially on their previous networks for their recruitment strategies, as they are much more likely to recruit from their networks than would happen at random. This finding relates to the significant impact of referrals and social connections of incumbent employees on new hires (Cingano and Rosolia, 2012; Kramarz and Skans, 2014; Dustmann et al., 2016; Glitz, 2017). While previous research largely relies on administrative data and focuses on the social ties of employees, we show that the manager's network plays a major role. Furthermore, we observe that managers use their networks to recruit squad players (as opposed to star players) at a lower price than their market value (Groysberg et al., 2008; Teece, 2003; Carnahan et al., 2012). This focus on non-star players may reflect strategic adaptation to the well-documented challenges of hiring external stars, whose performance tends to be context-dependent and often fails to transfer across organizations (Groysberg et al., 2004). Our findings suggest that managers may use private information to identify undervalued talent. This informational advantage may be particularly valuable for non-star players, where publicly available signals are noisier and managers' knowledge of work habits, coachability, and fit provides a competitive edge. In this context, managers may even rely on single first-hand observations to make hiring decisions, see, e.g., Dalton and Landry (2020) in the NBA, suggesting that the depth of knowledge accumulated through direct supervision measured in our setting may be highly relevant. Overall, the findings shed some light on how managers may use private information from prior working relationships to benefit their new organization (Briscoe and Rogan, 2016; Mion et al., 2016; Patault and Lenoir, 2024).

Second, we find that players recruited through the manager's network tend to be given more responsibilities, measured through more games and minutes played. This finding is a novel addition to the literature, which has primarily focused on the impact of referrals and ties on the probability of finding a job (Kramarz and Skans, 2014; Glitz, 2017) or improved labor conditions such as wages, full-time jobs, or other advantages (Saygin et al., 2021; Barwick et al., 2023). Our data, however, allows us to compare how managers use workers recruited from the network compared to other workers under similar competitive conditions. As Fenizia (2022) and Minni (2026), we can also observe the manager-employee relationship over time. We find that workers recruited from the managers' network have an advantage, regarding responsibilities, that decreases with time. Specifically, the positive effect on responsibilities is predominantly driven by players recruited during the manager's first year, while negative effects emerge for players recruited in the manager's later years at the club.

Our interpretation is that the uncertainty channel is a key driver. The mobility of managers has long been associated with implementing new high-order organizational routines and practices (Kraatz and Moore, 2002; Campbell et al., 2012). However, the implementation process often involves uncertainty, results in false starts, and requires time. Under these circumstances, new managers may rely on workers from their network to establish organizational routines and practices (Mawdsley and Somaya, 2016). As former mobile workers have tacit knowledge and experience with such routines, their input becomes essential in effectively transferring key routines impacting performance (Aime et al., 2010). Once the desired routines and practices are successfully established and all workers gain experience with the manager, the relevance of former workers from the network diminishes. However, alternative explanations cannot be ruled out. On the one hand, managers may have elevated expectations for network hires or feel compelled to justify their recruitment investment by allocating more playing time initially, with these pressures diminishing over time. On the other hand, organizational transition costs may cause network hires to underperform in their first season and consequently receive less playing time in the subsequent seasons. Individual-level performance data would help distinguish between these mechanisms.

Third, we examine the influence of players hired from the managers' network on team performance. The literature is scarce because detailed firm and employee performance data is not easily available. Some research links hiring through referrals with nepotism, lack of diversity, and biases that can negatively impact the best-qualified candidates and hurt organizational performance (Beaman and Magruder, 2012; Beaman et al., 2018; Ertug et al., 2020). However, several studies show evidence that firm performance benefits from employee referrals increasing production (Eliason et al., 2017), reducing turnover or recruitment costs (Burks et al., 2015), or increasing growth rates (Barwick et al., 2023). In football, as in other industries, network hiring is accepted when successful but criticized when recruits underperform. For example, some team members may become more critical of network hiring when facing negative results and undermine team cohesion. This social cost, in addition to the monetary costs from hiring players (transfer fees, wages, etc.) incentivizes managers to be selective with network hires. We find that hiring more workers from the manager's network is associated with higher firm performance, measured by the number of points at the end of the season and league ranking. Throughout these results, we find remarkably similar results for men and women.

The analysis presented above could suffer from several limitations. First, all our analysis is purely observational. Confounds may influence our results. For example, managers with more control over the firm's hiring process—and thus recruit more players in their network—could also have more ability to shape the team and not suffer from external pressure from owners and others in higher management, leading to higher firm performance. Similarly, our definition of managers' networks could be masking the fact that other people from the team participate in the identification and hiring of new talent, such as the assistant manager, scouts, or the sporting director. Additionally, other ties might exist between managers and players, such as being represented by the same agents, and might be partially confounding our results.

Second, while we can study transfers between firms in detail, including associated fees, we lack salary information. While managers may be able to recruit players in their network at lower prices, it could be that these players have more bargaining power in salary negotiations, and therefore, the reduction in transfer fees could be offset by higher salaries to be paid to the players.

Third, while our data can capture the responsibilities given to workers in the most relevant events (games), we cannot observe how managers and players interact daily in training. Empirical evidence on how players recruited from the manager's network transmit ideas, build strategies, and create knowledge remains a challenge for future research.

Finally, the present paper focuses on a very specific corner of the world. We specify the generalizability of our findings for firms and managers in other industries in their incentives, beliefs, and constraints (List, 2020). Regarding beliefs, one important feature of the football industry is that there is very little uncertainty regarding the tasks of workers across teams (Dietl et al., 2011; Pieper et al., 2014; Gomez-Gonzalez et al., 2019), which enabled us to make comparisons across time, teams, and countries. However, in other markets, assuming that more uncertainty exists about the transferability of skills from one employer to the next is not unreasonable (Dokko et al., 2009; Raffiee and Byun, 2020). In such cases, managers might not be able to resolve the information asymmetry problem substantially, and their ability to identify productive workers for their new employer might therefore be reduced. Understanding how networks can be leveraged to cope with uncertainty in different organizational settings would be an interesting avenue for future research.

Additionally, professional football provides managers with more publicly observable information about worker performance than most industries, i.e., match statistics, scouting reports, and market valuations. That we find managers still rely heavily on their former employees despite this wealth of public data suggests their private knowledge, e.g., about work ethic, reliability, or coachability, provides substantial value. In industries with less transparent and readily available performance metrics, reliance on network-based information is likely even more important. In this regard, our results could be seen as lower-bound estimates for the effects of managers' networks on employee recruitment.

Another important feature of the European football market, which relates to the incentives in the industry, is its highly competitive nature, with managers facing considerable pressure (reflected in how the median tenure with a team is less than a year). This means that managers' incentives depend greatly on the performance of their network-recruited workers, which has been found to induce a better selection of referrals (Beaman and Magruder, 2012). We believe that for our results to be applicable to other contexts, we would need similar types of strong alignment of incentives. One potential parallel could be found in the consulting industry, where the competitive nature of the market, reliance on personal networks for recruitment, and performance-driven incentives may similarly shape the quality and effectiveness of referrals.

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Appendices

A Transfer maps

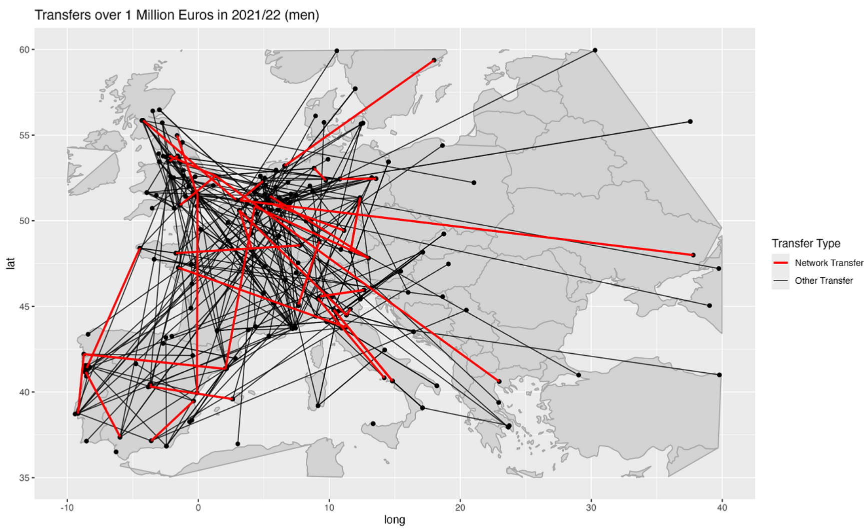

Figure A.1: All transfers with a fee exceeding €1 million in the 2021/2022 season (men's sample). Source: own calculation based on transfermarkt.com.

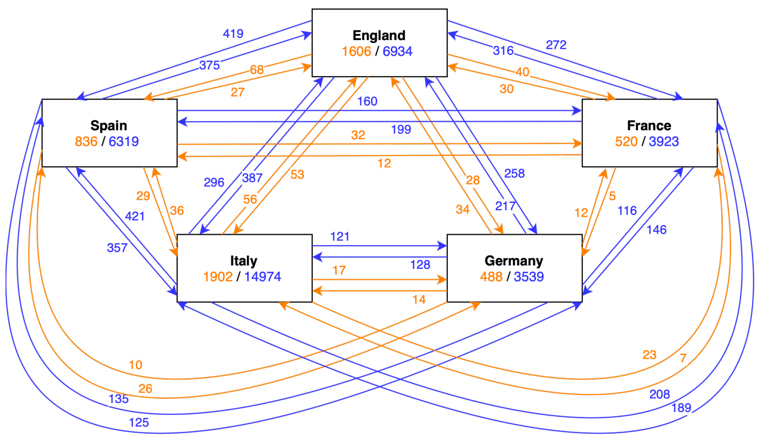

Figure A.2: Number of transfers between "Big Five" leagues (England, France, Germany, Italy and Spain, men's sample). Source: own calculation based on transfermarkt.com.

Note: Blue links and blue numbers correspond to transfers outside networks. Orange links and orange numbers correspond to transfers within networks. Numbers within one country correspond to transfers between clubs of the same country. All seasons in our data are included (2008/2009 to 2021/2022).

B Robustness checks

Table B.1: Prevalence of within-network transfers: Robustness with different definitions of the random network

Definition network (1)	N (2)	Nb coaches per player (3)	Nb possible teams (4)	Probability at random (5)	Share in data (6)	Ratio (7)
Baseline (men)	95,063	5.10	570	0.009	0.107	11.92***
Baseline (women)	18,328	1.73	1433	0.001	0.008	7.02***
Only within-country transfers (men)	47,035	5.10	62.1	0.082	0.115	1.40***
Only international transfers (men)[1]	11,006	5.10	507.9	0.010	0.090	8.99***
Only counting non-free transfers	13,193	5.10	570	0.009	0.057	6.32***
Only counting free transfers	31,592	5.10	570	0.009	0.030	3.36***
First year of coach tenure (men)	64,912	5.10	570	0.009	0.062	6.93***
Later years of coach tenure (men)	30,151	5.10	570	0.009	0.203	22.66***
Restricting link to 1 year	95,063	5.10	570	0.009	0.067	7.52***
Restricting link to 3 years	95,063	5.10	570	0.009	0.089	9.93***
Restricting link to 5 years	95,063	5.10	570	0.009	0.098	10.95***

Note: Column 2 represents the number of transfers considered; Column 3 represents the average number of coaches a players has on his or her career; Column 4 represents the number of possible teams for a transfer; Column 5 represents the probability of a player joining a former coach, under a random network, defined by (3)/(4); Column 6 represents the actual share of players transferred within the manager's network in the data; Column 7 represents the ratio of (6)/(5). The significance levels represent the likelihood of observing the actual share (Column 6) under the null hypothesis of the probability being that of Column 5. The *Restricting link to X years* rows restrict the within network variable to be valid if last relationship between the player and the coach is less than X years old. * p < 0.1; **p<0.05; ***p<0.01. [1]: This network definition only counts transfers between clubs in the data base (not transfers into the studied leagues).

Table B.2: Hiring by tenure of coach

	Log market value (1)	Fee - Market value (2)
Transfer from network	-0.155^{***}	-80.409
	(0.020)	(74.627)
First Year	-0.085^{***}	71.203
	(0.015)	(50.084)
Transfer from network × First Year	0.102^{***}	-17.465
	(0.027)	(106.557)
Age	0.053^{***}	-99.408^{***}
	(0.002)	(8.860)
Constant	4.576^{***}	$1{,}732.127^{***}$
	(0.256)	(259.270)
Observations	77,204	38,532
R^2	0.543	0.084

Note: The dependent variable in Column 1 is the market value of the player at the time of transfer In Column 2, the dependent variable is the difference between what the team pays for the player and the market value. Both variables are coded in thousands of euros. The Transfer from Network variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. The variable First Year is a dummy variable equal to 1 if the transfer occurred within the first year of the coach tenure at the club. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Robust standard errors clustered at the team level. * $p < 0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table B.3: Hiring decisions: robustness with alternative specifications

	Men		Women	
	Market value	Fee	Market value	Fee
	(1)	(2)	(3)	(4)
Transfer from network	-239.732^{***}	-58.901	8.481	-2.195
	(59.183)	(48.806)	(7.064)	(1.878)
Market value		0.785^{***}		0.112
		(0.046)		(0.099)
Age	29.212^{***}	-100.890^{***}	1.569^{***}	-0.325^{*}
	(4.376)	(8.924)	(0.254)	(0.193)
Constant	-123.491	$1{,}958.165^{***}$	-22.816^{**}	6.841
	(243.937)	(252.894)	(9.947)	(8.215)
Position FE	✓	✓		
Nationality FE	✓	✓	✓	✓
Team FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	77,204	38,532	1,615	1,615
R^2	0.407	0.689	0.424	0.251

Note: The dependent variable in Columns 1 and 3 is the metric for quality of workers, represented by the market value of the player at the time of the transfer. In Columns 2 and 4, the dependent variable is what the team pays for the player and we control for the market value. Both variables are coded in thousands of euros. The *Transfer from network* variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. *Nationality FE* captures the player nationalities and the nationality tie between the manager and the player. Robust standard errors clustered on the team level. * $p < 0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table B.4: Quality of hiring (market value): Robustness by tie recency

	Men			Women		
	1 year	3 years	5 years	1 year	3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer from network 1 year	−0.139***			0.276*		
	(0.019)			(0.153)		
Transfer from network 3 years		−0.100***			0.274	
		(0.016)			(0.189)	
Transfer from network 5 years			−0.084***			0.274
			(0.015)			(0.189)
Age	0.053***	0.053***	0.053***	0.046***	0.046***	0.046***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Constant	4.496***	4.483***	4.476***	1.729***	1.724***	1.724***
	(0.256)	(0.254)	(0.254)	(0.238)	(0.234)	(0.234)
Position FE	✓	✓	✓			
Nationality FE	✓	✓	✓	✓	✓	✓
Team FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Observations	77,204	77,204	77,204	1,614	1,614	1,614
R^2	0.543	0.542	0.542	0.556	0.557	0.557

Note: The dependent variable is the log of the market value of the player, used as a metric for player quality. The variable is coded in thousands of euros. The Transfer from Network variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. This variable is restricted to the link being no more than X years for the corresponding columns. The dataset for women comprises only 5 years, meaning that the overlap between the 3 and 5 year windows is nearly identical (and the overlap between the 5-year window and the entire window (baseline) is almost perfect). Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Robust standard errors clustered at the team level. * $p < 0.1$; **$p<0.05$; ***$p<0.01$.

Table B.5: Cost of hiring: Robustness by tie recency

	Men			Women		
	1 year	3 year	5 year	1 year	3 year	5 year
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer from network 1 year	−47.107			-9.712^{**}		
	(60.223)			(4.733)		
Transfer from network 3 year		−66.062			−9.728	
		(55.293)			(7.265)	
Transfer from network 5 year			−85.492			−9.728
			(54.631)			(7.265)
Age	-99.870^{***}	-99.796^{***}	-99.639^{***}	-1.713^{***}	-1.719^{***}	-1.719^{***}
	(8.943)	(8.924)	(8.899)	(0.291)	(0.290)	(0.290)
Constant	$1,818.622^{***}$	$1,822.398^{***}$	$1,822.070^{***}$	26.937^{**}	27.108^{**}	27.108^{**}
	(253.693)	(253.461)	(253.296)	(13.270)	(13.180)	(13.180)
Position FE	✓	✓	✓			
Nationality FE	✓	✓	✓	✓	✓	✓
Team FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Observations	38,532	38,532	38,532	1,615	1,615	1,615
R^2	0.084	0.084	0.084	0.333	0.333	0.333

Note: The dependent variable is the transfer fee minus market value, used as a metric for the price the new team buys the player. The variable is coded in thousands of euros. The Transfer from Network variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. This variable is restricted to the link being no more than X years for the corresponding columns. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Robust standard errors clustered at the team level. * $p < 0.1$; **$p<0.05$; ***$p<0.01$.

Table B.6: Hiring decisions: robustness with other characteristics

	Men		Women	
	Lagged Minutes	Age	Lagged Minutes	Age
	(1)	(2)	(3)	(4)
Transfer from network	-154.823^{***}	0.605^{***}	212.286^{***}	0.759
	(21.952)	(0.064)	(73.139)	(0.481)
Constant	617.624	22.389^{***}	$1{,}535.625^{***}$	22.505^{***}
	(443.325)	(0.412)	(95.027)	(1.082)
Position FE	✓	✓		
Nationality FE	✓	✓	✓	✓
Team FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	70,641	94,922	4,659	17,227
R^2	0.071	0.123	0.334	0.347

Note: The dependent variable in Columns 1 and 3 is the number of minutes played in the season prior to the transfer. In Columns 2 and 4, the dependent variable is the age of the player at the time of the transfer. The Transfer from Network variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Robust standard errors clustered at the team level. * $p < 0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table B.7: Hiring decisions, by transfer fee

	Transfer fee > 0		Transfer fee $= 0$
	Log Market value	Fee - Market value	Log Market value
	(1)	(2)	(3)
Transfer from network	0.133^{***}	-224.025^{*}	0.013
	(0.031)	(117.513)	(0.018)
Age	0.060^{***}	-247.556^{***}	0.045^{***}
	(0.004)	(22.253)	(0.002)
Constant	4.966^{***}	$5{,}219.182^{***}$	4.709^{***}
	(0.256)	(771.335)	(0.324)
Position FE	✓	✓	✓
Nationality FE	✓	✓	✓
Team FE	✓	✓	✓
Season FE	✓	✓	✓
Observations	12,786	12,786	25,746
R^2	0.566	0.115	0.523

Note: The dependent variable in Columns 1 and 3 is the metric for quality of workers, represented by the log market value of the player at the time of the transfer. In Column 2, the dependent variable is the difference between what the team pays for the player and the market value. Both variables are coded in thousands of euros. Columns 1 and 2 restrict the sample to transfers with a positive transfer fee. Column 3 restricts to free transfers. The Transfer from Network variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Robust standard errors clustered at the team level. * p < 0.1; **p<0.05; ***p<0.01.

Table B.8: Responsibilities: Robustness by tenure of coach

	Recruitment in first year		Recruitment in later years	
	Minutes played	Games played	Minutes played	Games played
	(1)	(2)	(3)	(4)
Tenure	66.680***	0.764***	71.310***	0.825***
	(3.787)	(0.045)	(3.873)	(0.046)
Social tie first year	113.639***	0.997**		
	(34.382)	(0.442)		
Social tie first year	5.981	−0.022		
× Tenure	(35.910)	(0.467)		
Social tie later years			72.536*	0.647
			(37.952)	(0.505)
Social tie later years			−206.968***	−2.601***
× Tenure			(23.773)	(0.309)
Constant	−5,418.617***	−49.859***	−5,410.242***	−49.724***
	(817.178)	(10.179)	(813.868)	(10.184)
Individual controls	✓	✓	✓	✓
Position FE	✓	✓	✓	✓
Nationality FE	✓	✓	✓	✓
Team FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	106,045	106,045	106,045	106,045
R^2	0.127	0.123	0.129	0.125

Note: The dependent variable in Columns 1 and 3 is the number of minutes played over a season. In Columns 2 and 4, the dependent variable is the number of games played in a given season. The Social tie variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer, for every season following the transfer. The social tie is set to 1 in first year if the player was recruited by their former manager in the first year of the new position for the manager at the team. The Tenure variable represents the number of years the player has been playing for the club. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Individual controls include market value, age and age squared. Robust standard errors clustered at the team level. * $p < 0.1$; **$p<0.05$; ***$p<0.01$.

Table B.9: Responsibilities: Robustness by tie recency (minutes)

	Men			Women		
	1 year	3 years	5 years	1 years	3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)
Tenure	71.504***	71.834***	72.165***	−7.645	−9.828	−9.822
	(3.880)	(3.884)	(3.888)	(48.395)	(48.563)	(48.564)
Social tie 1 year	71.281*			131.728		
	(41.927)			(84.849)		
Social Tie 1 year	−218.827***			110.625		
× Tenure	(23.751)			(125.637)		
Social tie 3 years		92.834***			156.162**	
		(30.158)			(71.312)	
Social Tie 3 years		−202.703***			207.429	
× Tenure		(21.599)			(126.760)	
Social tie 5 years			114.443***			155.221**
			(28.300)			(69.461)
Social Tie 5 years			−199.091***			208.319*
× Tenure			(20.439)			(125.951)
Constant	−5,421.067***	−5,424.854***	−5,419.225***	−1,547.502***	−1,546.933***	−1,546.583***
	(816.206)	(816.767)	(817.139)	(379.287)	(379.108)	(379.095)
Individual controls	✓	✓	✓	✓	✓	✓
Position FE	✓	✓	✓	✓	✓	✓
Nationality FE	✓	✓	✓	✓	✓	✓
Team FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Observations	106,045	106,045	106,045	17,277	17,277	17,277
R^2	0.129	0.129	0.129	0.276	0.277	0.277

Note: The dependent variable is the number of minutes played in a given season, used as a metric for responsibilities given to the player. The Social tie variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer, for every season following the transfer. This variable is restricted to the link being no more than X years for the corresponding columns. The Tenure variable represents the number of years the player has been playing for the club. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Individual controls include market value and age. Robust standard errors clustered at the team level. * p < 0.1; **p<0.05; ***p<0.01.

Table B.10: Responsibilities: Robustness by tie recency (games)

	Men			Women		
	1 year	3 years	5 years	1 years	3 years	5 years
	(1)	(2)	(3)	(4)	(5)	(6)
Tenure	0.826***	0.829***	0.833***	−0.436	−0.465	−0.464
	(0.046)	(0.046)	(0.046)	(0.522)	(0.524)	(0.524)
Social tie 1 year	0.390			1.377		
	(0.572)			(0.951)		
Social Tie 1 year × Tenure	−2.655***			1.663		
	(0.311)			(1.371)		
Social tie 3 year		0.714*			1.342*	
		(0.408)			(0.766)	
Social Tie 3 year × Tenure		−2.495***			3.097**	
		(0.278)			(1.421)	
Social tie 5 year			1.027***			1.435*
			(0.379)			(0.748)
Social Tie 5 year × Tenure			−2.473***			3.005**
			(0.263)			(1.414)
Constant	−49.733***	−49.842***	−49.809***	−13.716***	−13.710***	−13.707***
	(10.193)	(10.199)	(10.205)	(4.378)	(4.376)	(4.376)
Individual controls	✓	✓	✓	✓	✓	✓
Position FE	✓	✓	✓	✓	✓	✓
Nationality FE	✓	✓	✓	✓	✓	✓
Team FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Observations	106,045	106,045	106,045	17,277	17,277	17,277
R^2	0.125	0.125	0.125	0.352	0.352	0.352

Note: The dependent variable is the number of games played in a given season, used as a metric for responsibilities given to the player. The Social tie variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer, for every season following the transfer. This variable is restricted to the link being no more than X years for the corresponding columns. The Tenure variable represents the number of years the player has been playing for the club. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Individual controls include market value and age. Robust standard errors clustered at the team level. * $p < 0.1$; ** $p<0.05$; *** $p<0.01$.

Table B.11: Evolution in players' valuation

	Men	Women
	(1)	(2)
Social tie	120.421**	−8.011
	(55.639)	(14.655)
Tenure	423.941***	−4.047
	(61.899)	(3.916)
Social Tie × Tenure	−270.245***	
	(90.965)	
Constant	−3,429.424***	−25.825
	(789.279)	(45.750)
Observations	76,105	858
R^2	0.137	0.505

Note: The dependent variable is the difference between the market value in season t and the market value at the time of the transfer to the team. The Social tie variable is a dummy variable equal to 1 if the player had been coached by the manager prior to the transfer, for every season following the transfer. The Tenure variable represents the number of years the player has been playing for the club. Nationality FE captures the player nationalities and the nationality tie between the manager and the player. Individual controls include market value, age and age squared. Robust standard errors clustered at the team level. * $p < 0.1$; **$p<0.05$; ***$p<0.01$.

Table B.12: Firm Performance robustness: Share of recruited players

	Men		Women	
	Total points	Rank	Total points	Rank
	(1)	(2)	(3)	(4)
Network transfers (%)	0.231***	0.089***	−0.768	−0.127
	(0.029)	(0.009)	(0.748)	(0.181)
Network transfers (%) sq	−0.002***	−0.001***	0.056*	0.004
	(0.001)	(0.0002)	(0.032)	(0.007)
Constant	32.426***	−21.000***	16.060***	−8.783***
	(6.746)	(1.921)	(1.437)	(0.357)
Team FE	✓	✓	✓	✓
League FE	✓	✓	✓	✓
Divison FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	6,421	6,421	483	483
R^2	0.588	0.490	0.824	0.806

Note: The dependent variable in Columns 1 and 3 is the number of points a team got in a season. In Columns 2 and 4, the dependent variable is the opposite of the rank, meaning that an increase in the dependent variable corresponds to a better rank. The variable Network transfers (%) is the percentage of players transferred in the current transfer window from the coach's network. Robust standard errors clustered on the team level. The number of observations in this Table is lower than in Table 5 because teams that did not make any transfers in a given season are excluded from the analysis (share of network transfers undefined).

Table B.13: Firm Performance robustness: Share of recruited players

	Men		Women	
	Total points	Rank	Total points	Rank
	(1)	(2)	(3)	(4)
Nb players from network	0.882***	0.343***	−2.985	−0.377
	(0.158)	(0.064)	(2.035)	(0.579)
Nb players from network sq	−0.064***	−0.024***	0.789*	0.092
	(0.019)	(0.008)	(0.417)	(0.108)
Average points	2.409***		−1.241**	
	(0.202)		(0.613)	
Average rank		−2.027**		−2.377
		(0.960)		(2.419)
Constant	−81.430***	−40.216***	87.185***	−17.787
	(11.871)	(9.262)	(22.490)	(20.731)
Team FE	✓	✓	✓	✓
League FE	✓	✓	✓	✓
Divison FE	✓	✓	✓	✓
Season FE	✓	✓	✓	✓
Observations	6,424	6,424	2,228	2,228
R^2	0.579	0.480	0.811	0.823

Note: The dependent variable in Columns 1 and 3 is the number of points a team got in a season. In Columns 2 and 4, the dependent variable is the opposite of the rank, meaning that an increase in the dependent variable corresponds to a better rank. The variable Network transfers (%) is the percentage of players transferred in the current transfer window from the coach's network. Robust standard errors clustered on the team level. The number of observations in this Table is lower than in Table 5 because teams that did not make any transfers in a given season are excluded from the analysis (share of network transfers undefined).

C Characteristics of managers who recruit more players within networks

Table C.1: Manager characteristics and share of network-recruited workers

	Men	Women
	(1)	(2)
Nb of positions in career	-0.005^{***}	-0.003
	(0.001)	(0.002)
Nb players in career	0.00001	0.0003^{***}
	(0.0001)	(0.0001)
Nb seasons in career	0.007^{***}	0.016^{***}
	(0.001)	(0.003)
Constant	0.028	-0.015
	(0.049)	(0.011)
Nationality FE	✓	✓
Observations	3,005	2,784
R^2	0.105	0.183

Note: The dependent variable is the share of players recruited through the manager's network during his or her career. * p < 0.1; **p<0.05; ***p<0.01.