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Job Matches and Mobility of High Wage Workers in an International Labor Market

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Abstract

We examine worker-to-firm matching in a high-wage international labor market encompassing nine European countries. Employment matches are ranked along two key dimensions: worker productivity, defined by contributions to physical output, and firm productivity, measured by the ability to generate revenue from that physical output. We find a strong and significant positive rank correlation between these two measures, both within and across countries. This evidence of 'positive assortative matching' suggests that labor market frictions do not prevent high-productivity workers from matching with high-productivity firms across Europe. Both workers' initial job placements and their subsequent mobility within countries and across countries reinforce this pattern.

Keywords: assortative matching, international worker mobility, football managers
JEL-codes: M51, J63, J24, Z22

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1 Introduction

A common prediction in economic models of the labor market is that relatively more productive firms will employ relatively more able workers, and likewise, that less productive firms end up with less able workers (Eeckhout (2018)). If there are complementarities between workers and firms in production, more productive firms have more to gain from hiring high ability workers and will therefore offer them higher wages. Low productivity firms are unable to match these wage offers and hence fail to retain the high ability workers they might initially recruit. This process leads to 'positive assortative matching' between workers and firms in labor market equilibrium. If labor market frictions hamper worker mobility, they distort this matching process which may cause large efficiency losses, especially if there are strong complementarities in production (see Eeckhout and Kircher (2011) and Bagger and Lentz (2019)).

Even though formal restrictions on labor mobility in Europe have steadily been reduced, national borders still play an important role in the European labor market (Dorn and Zweimüller (2021)). Cross-border correlations in unemployment rates and GDP per capita suggest that language and cultural borders rather than physical borders hinder labor market integration (Bartz and Fuchs-Schündeln (2012)). As a result of these barriers, European workers act as if their human capital is very heavily taxed by moving countries (Head and Mayer (2021)). Moreover, evidence related to a Swiss labor market reform suggests that granting cross-border workers free access only has employment effects in regions very close to the border (Beerli et al. (2021)). The question remains whether national borders play an equally important role in high wage labor markets, where the economic surplus of a good worker-firm match (and loss from a bad match) is more substantial than in the labor market at large.

In this paper we analyze the strength and direction of assortative matching in a high wage international labor market: the European labor market for football managers.[1] Football is a sport where two teams of eleven players play matches against each other. National competitions are typically organized as a round-robin tournament, in which each team plays every other team twice over the course of a season, once at home and once away. A match lasts 90 minutes plus stoppage time. The objective is to score goals while

[1]The word "manager" is typically used in British professional football, whereas in continental Europe often the terms "coach", "head coach" or "trainer" are used for the person who is responsible for the performance of a team. We stick to using the British term throughout this paper.

preventing the opposing team from scoring. A goal is awarded when the ball completely crosses the goal line between the goalposts and beneath the crossbar.

The team that scores most is the winner of the match. If both teams score the same amount of goals there is a draw. We therefore use the goal difference as the measure of sporting success, which we consider as the physical output of the firm. Some aspects of sporting success are player-driven, some aspects are team driven and some aspects are manager-driven. Hence, we measure the worker productivity of the manager as their contribution to the goal difference. For clubs, sporting success leads to higher revenues through the increase in TV revenues, prize money, attendance, merchandise and so on. We combine data on sporting success and club revenues to estimate the marginal revenue increase of an improvement in sporting performance. The club's ability to translate sporting success into monetary revenues is our measure of firm productivity.

In our analysis, we collected data from three different sources. First, data of outcomes at the level of individual matches. Second, information about names and individual characteristics of managers. Third, seasonal financial data of clubs. Our dataset tracks worker-firm matches, i.e., manager-football club matches, across nine European countries for 12 consecutive years. The number of worker-firm matches per year is around 180, which gives a total of 2,150 observations overall. They involve 551 unique workers (managers) employed by 297 unique employers (clubs). In the football industry, we separately observe the physical output (sporting results) and monetary output (club revenues) of the firm. This allows us to quantify worker productivity as the skill to generate physical output from inputs (player wages, home advantage) and gauge firm productivity by the amount of revenues firms generate from a given amount of physical output (sporting results). We establish these independent worker and firm productivity rankings for each year in our dataset. The rank correlation between worker and firm productivity in the observed employment matches is our measure of assortative matching. In our dataset, this rank correlation is positive and significant both within countries and across the entire international labor market. We interpret this as evidence for positive international assortative matching. The match surplus created in the European labor market is large enough to overcome potential frictions imposed by national borders. A further analysis of worker mobility patterns reveals that positive assortative matching arises through a combination of the initial allocation of workers to firms and the upward (international) mobility of highly productive workers both within and between countries.

There are several benefits of analyzing sports data to understand economic mechanisms including the functioning of labor markets (Palacios-Huerta (2025)). The data we use provide frequent and public observations on the performance of clubs and managers. Furthermore, football managers experience a lot of turnover working at several clubs during their career. This allows us to study the matching between managers and firms in detail. An important advantage of our data is that we observe both worker-level productivity and firm-level financial information. Nevertheless, using sports data may come at the cost of a lack of external validity if the economic phenomenon investigated is sport-specific. We argue that this is not the case here. Although some of the characteristics of the football manager labor market are unique, international migration is common in high-skilled professions near the top of the earnings distribution. In this regard, football managers are similar to e.g. academic researchers, entertainers and managers in executive boards.

Our contribution to the empirical literature on assortative matching is twofold. First, we look at assortative matching across countries, i.e. we consider matching at national levels and at the level of an international labor market. Second, we show that positive assortative matching has positive assortative mobility as an important determinant. When high-productivity workers change jobs, they are more likely to move to high productivity firms. This is irrespective of whether mobility is within countries or between countries. We also show that it is helpful in the analysis of assortative matching to obtain separate estimates of the productivity of workers and firms.

The rest of our paper is set-up as follows. In Section 2 we present an overview of previous studies on the European labor market for football managers and assortative matching. Section 3 describes the data we use in the analysis. In Sections 4 we discuss the estimation of worker and firm productivity rankings. In Section 5 we present estimates of assortative matching between workers and firms in international football. In Section 6 we analyze worker mobility. In Section 7 we present a range of sensitivity analyses to show the robustness of our findings. Section 8 concludes.

2 Related Literature and Setting

2.1 European Labor Market for Football Managers

In our empirical analysis we study the European labor market for football managers. A football manager's main responsibility is to maximize the performance of the club's players on the pitch. To achieve this, professional football managers perform typical management functions such as selecting players for the game line-up, motivating the team, resolving conflicts between players, and developing training routines. Managers may also be consulted in more strategic decisions, such as player recruitment and youth development, but they are not involved in the commercial activities of the club (see Kelly (2017)). Hence, we can separate the manager's contribution to team success on the field from the club's ability to translate its sporting performances into revenues.

From a research perspective, four features of the labor market for football managers warrant further attention. First, the performance of a club and thus of a manager is a matter of public record, such that competing firms as well as researchers can readily observe it.[2] Football clubs play at least once per week, such that information on a manager's ability is quickly revealed. Clubs appear to use this public information on worker performance in their employment decisions, as they fire their under-performing managers (Van Ours and van Tuijl (2016), Bryson et al. (2024)) and poach over-performing managers from rival firms (Peeters et al. (2022)).

Second, although football clubs have many workers – players, medical staff, assistant managers, and so on – at each point in time a club employs only one manager who has overall responsibility. It is the productivity of the manager that affects the performance of the club. This means we can clearly ascribe the performance of the team to a specific worker. In linked employer-employee data sets each firm typically has many workers, which makes it more difficult to measure the correlation between a firm's productivity ranking and the productivity of the various workers. Since we focus on the worker that has overall responsibility we do not encounter this problem here.

Third, football managers experience a lot of job turnover and typically work for multiple clubs during their career. This mobility creates the variation we need to separate the ability of managers from the capability of their employers. Vacancies are filled quickly

[2]For example, Muehlheusser et al. (2018) leverage this public information to estimate the heterogeneity in managerial ability in the highest tier of professional football in Germany, the Bundesliga.

such that the tenure of interim workers (or 'caretaker' managers) is no more than a couple of weeks. Employment contracts are defined in terms of football seasons, which run from early August until late May. The off-season (June-July) is a natural breaking point and provides firms and workers with the opportunity to form new matches if they think they can improve upon their current match. We therefore draw our annual sample of employment matches at the first game of a new season, right after the labor market matching process has completed.

Finally, the social costs of moving from one European country to another may be lower for football managers than for many other professionals. For example, for an average worker communication with co-workers in a different country may not be easy because of differences in language and culture. For a football manager, this is less problematic as most clubs have a multinational workforce and therefore football has a universal language and culture. Still, Peeters et al. (2021) find that cultural distance may decrease the effectiveness of a migrant manager when working abroad. Likewise, occupational licensing may distort workers' opportunities to practice their profession abroad or even across US states (Johnson and Kleiner (2020)). In our setting, this is not an issue, because UEFA introduced homogeneous occupational licenses for professional football managers from the 2003/04 season onward (Kelly (2017)). According to economic theory, a worker will compare the cost of migrating and the expected benefits of doing so. As for other high skilled professionals, such as inventors, university professors and CEOs, a football manager's contract in a foreign country will more often than not be in the top of the earnings distribution. This means that benefits will be substantial even if most labor contracts are short term, typically no more than a couple of years.

Our paper is not the first to use European football as a setting to investigate worker migration. Kleven et al. (2013) study migration patterns of professional football players in response to differences in tax rates among European countries. They find a strong mobility response to tax rates with low taxes attracting high ability workers who displace low ability workers and low taxes on foreign workers displacing domestic workers. Our approach extends this analysis by considering assortative matching as an additional force to explain the migration of professional football managers. Bryson et al. (2014) studying job mobility of professional football players find that foreign players who migrated into Italy have a substantial wage premium which is attributed to foreign players having a superstar status.

Other papers using sports data to study assortative matching include Gandelman (2008) and Filippin and van Ours (2015), who find positive assortative matching in datasets on Uruguayan football players and Italian marathon runners. Both Drut and Duhautois (2017) and Scarfe et al. (2020) estimate worker and firm effects with the traditional two-way fixed effects approach a la Abowd et al. (1999). Using wage data of professional football players from the Italian and US leagues, respectively, they find contradicting results with a positive correlation between worker and firm effects for Italy, but a negative correlation for the US.

2.2 Assortative Matching Literature

Despite its prevalence in theoretical models and intuitive appeal, it has proved challenging to confirm the presence of positive assortative matching between workers and firms in empirical research. Following the seminal paper of Abowd et al. (1999), researchers used to examine assortative matching through the correlation between worker and firm fixed effects estimated in a wage equation.[3] The surprising conclusion from this approach was that matching is either not assortative, or even negatively assortative in some analyses (Andrews et al. (2008)). In an attempt to explain this apparent anomaly, subsequent research focused on theoretical and empirical issues with the use of two-way wage fixed effects (see Gautier and Teulings (2006), Andrews et al. (2008), Eeckhout and Kircher (2011), Lopes de Melo (2018), Jochmans and Weidner (2019), Bonhomme et al. (2023)). A critical problem uncovered by this line of research is that drawing the worker and firm effects from the same regression model (e.g., the worker's wage equation) leads to a downward bias in the correlation between both constructs, the so-called 'limited mobility bias' (Andrews et al. (2008), Jochmans and Weidner (2019)).

In response to the criticism on the Abowd et al. (1999) approach, researchers looked for other empirical methods to gauge the degree of assortative matching. Kline et al. (2020) introduce a leave-out estimation algorithm, which reduces the bias in the estimated correlations of the two-way fixed effects estimator. Other authors (Hagedorn et al. (2017) and Bagger and Lentz (2019)) build structural models which exploit worker transitions, either from unemployment or between jobs (poaching), to identify independent rankings of workers and firms. Bonhomme et al. (2019) propose a method to reconcile this structural approach with tractable estimation methods. They classify firms into groups

[3] See Bonhomme et al. (2026) for a recent state-of-the-art overview of the AKM model.

before estimating the full earnings model using maximum likelihood. Each of these papers finds significant positive assortative matching when they apply their method to real-life matched employer-employee data sets. A third strand of the literature looks for non-wage measures to establish independent worker and firm productivity rankings. Mendes et al. (2010) rank firms based on their estimated output productivity and workers by observed education level. Bartolucci et al. (2018) use profit data to establish a firm productivity ranking and wage data to rank workers. Again, both papers find strong evidence for positive assortative matching. Our methodology is inspired by the latter approach, as we leverage observations on physical versus monetary output production to construct separate worker and firm productivity rankings.

We contribute to the empirical matching literature by looking at assortative matching in a labor market that spans across national borders. Most previous studies rely on data obtained from matched employer-employee datasets drawn from national tax or social security administrations. While this generates a very complete picture of one particular national labor market, it is very difficult to match datasets from different national administrative sources to one another. Our solution is to focus on the labor market of football managers, where the mobility and personal characteristics of workers are well documented in popular sources and media reports. Building on Hoey et al. (2021), we source financial data on firms from the respective national firm registers. This allows us to construct an international matched employer-employee dataset with financial information on the employer side including annual payroll information. Unlike most papers in the literature however, we do not observe the individual salaries of the workers in our sample.

3 Data Sample and Sources

We collected data from three different sources: data of outcomes at the level of individual matches; information about names and individual characteristics of managers; seasonal financial data of clubs. We constructed a sample of the football manager labor market in nine European football federations: Belgium, England[4], France, Germany, Italy, the Netherlands, Portugal, Scotland and Spain. The sample starts in 2007-08, because our

[4]The UK has four distinct football federations and assorted league structures, England and Scotland (included here), plus Wales and Northern Ireland (not included).

financial data coverage is sufficient as of this season and ends in 2018-19 to avoid interference of the COVID-19 lockdown (see Bryson et al. (2021)). As such, our data consists of twelve repeated cross-sections. For each club, we observe which manager they employ in the first game of each season. This is a natural observation point as managers typically change employers over the summer football break. In-season switches are common, but they are usually the result of firings, which clubs believe will improve short-term performance (Van Ours and van Tuijl (2016), Bryson et al. (2024)). After in-season firings, clubs typically cannot hire their first choice managers, but are forced to choose from the currently unemployed set of managers. Hence, we prefer to investigate the employment matches emerging after a 'free' matching period, i.e. the summer break.

We collect data on all games played by the clubs during our sample period using the online archive footballdata.co.uk. We include both national league games and games in European competitions (Champions and Europa League) between clubs in the sample. We hand-collect the name of the manager in charge of each game from various sources including transfermarkt.com and wikipedia.com. We then add further personal characteristics on the manager (nationality, playing career, age) from the same sources. For the financial data we extend the database of Hoey et al. (2021) to include earlier seasons. For this we use the published financial statements of the clubs, the Orbis database from Bureau van Dijk, and the financial overview of the Direction Nationale de Controle de Gestion. For our analyses, we focus on the clubs' total annual revenues, tangible assets and total wage bill.[5]

As explained in more detail below, we need to observe the revenues of the club to estimate its productivity. For our estimates of worker productivity, we require that managers have a minimum number of matches in the data and that they are part of a connected network, i.e., they need to be sufficiently mobile to separately identify worker and firm effects (see Abowd et al. (1999)). We restrict our analysis to workers who have been active for at least 35 games in our sample. This corresponds to around one full year of employment.[6]

For all federations, our sample includes the top division. For larger federations with better financial data sources (England, France and Italy) we are also able to include the

[5]The vast majority of football clubs report financial data based on an accounting year running from July 1st through June 30th. This lines up with our sampling by football season. If clubs report in calendar accounting years, we recalculate the data to match football seasons. We use the pound to euro exchange rate on June 30th to convert accounts denominated in pounds to euros.

[6]We report results for alternative choices in sample selection in appendix A.

second tier. Football clubs may switch divisions between seasons due to promotion and relegation. Our sample is therefore unbalanced in terms of the employers we can include. The total number of worker-firm matches in our sample is 2,150 consisting of 551 unique workers and 297 unique firms.

4 Worker and Firm Productivity

Following Peeters et al. (2022), we measure the productivity of a worker, i.e., a manager, by his capacity to maximize the performance of the club on the field given the club's home advantage and the amount of playing talent the club employs. As such, the notion of worker productivity in this analysis resembles the idea of the teacher 'value-added' models used in the economics of education literature (e.g. Jackson (2013)).

We estimate this worker productivity, i.e., the productivity of football managers as follows. We model the goal difference[7] y_{ijt} at the end of the game between home team i and away team j played in league l in season t as follows:

$$y_{ijlt} = \beta_{hl} + \beta_{xl}(X_{it} - X_{jt}) + \gamma_i - \gamma_j + \mu_m - \mu_n + \varepsilon_{ijlt} \tag{1}$$

In equation (1), β_{hl} represents the average home advantage in league l, the vectors X_{it} and X_{jt} control for the playing talent both teams employ, measured by the logarithm of their annual payroll expenditure. Note that this refers to the total employment cost of all the club's employees.[8] The estimated parameter for playing talent β_{xl} is allowed to vary by the league in which the game takes place. A set of fixed effects for the teams (γ_i and γ_j) and managers (μ_m and μ_n) measure the contribution to the 'output' production of the two firms and two workers (managers) involved in the game. The worker fixed effects serve as the primary measure of worker productivity in the empirical analysis.

As shown by Abowd et al. (1999), both worker and firm fixed effects in equation (1) can be identified relative to a common benchmark when firms are connected to one another by mobile workers. Then, equation (1) can be estimated using standard linear estimation techniques. Through our data cleaning procedure we select the largest network

[7]Alternative output measures for football clubs are game outcomes and points gained. In our view, goal difference is a more detailed measure of output. We have repeated our analyses using these output measures as dependent variables in the worker effect regression. This does not change our results.

[8]Since the difference in log wage sums between the two teams is included this implies that inflation is accounted for since this affects both wage sums similarly.

of connected clubs in the sample and scale the worker fixed effects by the average over all workers. Implicit in equation (1) is the assumption that manager fixed effects are orthogonal to home advantage, i.e., home advantage is the same for all managers. In the estimation procedure we define the dependent variable as the goal difference from the perspective of the home team, meaning it is a positive if the home side won the game. We use linear restrictions on the coefficients of the log wage bill, club and manager effects to ensure they are exactly opposite for the home versus away team.[9]

Table 1: **Results Worker Productivity Model**

	Home advantage		Log wage	
European cups	0.49***	(0.04)	0.48***	(0.09)
Belgium D1	0.43***	(0.03)	0.72***	(0.14)
England D1	0.38***	(0.02)	0.42***	(0.11)
England D2	0.32***	(0.02)	0.42***	(0.07)
France D1	0.39***	(0.02)	0.53***	(0.09)
France D2	0.38***	(0.03)	0.38***	(0.10)
Germany D1	0.47***	(0.05)	0.62***	(0.16)
Italy D1	0.36***	(0.02)	0.57***	(0.08)
Italy D2	0.33***	(0.03)	0.26***	(0.09)
Netherlands D1	0.49***	(0.03)	0.40**	(0.15)
Portugal D1	0.37***	(0.04)	0.44***	(0.12)
Scotland D1	0.36***	(0.07)	0.65**	(0.28)
Spain D1	0.46***	(0.03)	0.33***	(0.09)
Explained variance				
Worker effects	$\frac{Cov(y,\mu)}{Var(y)}$	0.060		
Firm effects	$\frac{Cov(y,\gamma)}{Var(y)}$	0.042		
Other covariates	$\frac{Cov(y,X)}{Var(y)}$	0.097		
R-squared		0.198		
# Workers		567		
# Firms		307		
Observations		37,041		

Note: Observations at the game level. The dependent variable is goal difference defined from the perspective of the home team. Regression includes full sets of worker and firm fixed effects for home and away team. *** significant at 1% level, ** significant at 5% level.

We summarize the main estimation results of this analysis in Table 1. Home advantage is worth 0.3-0.5 goal difference and is significant in every country and division. Likewise,

[9] Alternatively, we can use every match twice. Once from the perspective of the home team and once from the perspective of the away team. In that case, we cluster the standard errors at the match level. These alternative estimates generate identical parameter estimates and similar standard errors.

the effect of the (log) wage sum is positive and significant throughout. Teams with higher overall employment costs tend to have more positive goal differences. On top of this, worker and firm fixed effects also contribute significantly to the explained variance in the goal difference. Our partitioning shows that the observables explain 9.7% of the variance, the club effects jointly explain 4.2% and the worker effects 6.0%. Both set of fixed effects are also jointly significant in a standard F-test. These results imply that worker productivity is important. Some managers are able to derive better sporting performance in similar circumstances presumably by making better decisions on the composition of the team, playing tactics, substitution of players during the match etc. The nature of the team fixed effects may refer to the scouting operation or youth development program of the club.[10]

We next estimate the revenue productivity for each firm (every football club). The revenue productivity is defined as the marginal revenue increase of an improvement in on-field performance. We model the revenues of club i playing in league l in season t, R_{it}, using a log-linear specification similar to the one used in Peeters and Szymanski (2014):

$$\log(R_{it}) = \beta y_{it} + \beta_x Z_{it} + \alpha_i + \lambda_l + \tau_t + \epsilon_{ilt} \tag{2}$$

In equation (2), y_{it} stands for the on-field performance of team i in year t, measured by the average goal difference per game. The control vector Z_{it} contains the log book value of the club's tangible assets and indicator variables for promoted and relegated clubs. Finally, the model includes three types of fixed effects, α_i, a firm-specific factor, which can be interpreted as the result of the club's history or marketing know-how, λ_l, a league-specific factor, which controls for league-wide revenue shifters such as the TV contract, and τ_t, a year effect to account for the growth of the football industry over time.

The parameter estimates of equation (2) are presented in Table 2. Better performing clubs have higher revenues. As expected, clubs with more tangible assets also have higher revenues. Relegated clubs have higher revenues while promoted clubs have lower revenues, conditional on other characteristics.

We measure firm productivity as the marginal revenue increase of an improvement in on-field performance. Using the estimates in Table 2 we calculate the additional revenues

[10]The firm effects may also represent a correction factor for measurement error in the manager fixed effects, as articulated by Andrews et al. (2008). We do not use these firm effects further in our main analyses.

Table 2: **Results Revenue Model**

Dep. Var.:	Log Annual Revenues	
Goal difference	0.157***	(0.015)
Tang. assets	0.078***	(0.007)
Promoted	-0.112***	(0.019)
Relegated	0.473***	(0.032)
Firm FE	Included	
League FE	Included	
Year FE	Included	
Explained variance		
Obs. co-variates	$\frac{Cov(y,X)}{Var(y)}$	0.139
Fixed effects	$\frac{Cov(y,FE)}{Var(y)}$	0.821
Total R-squared		0.959
Observations	2,453	

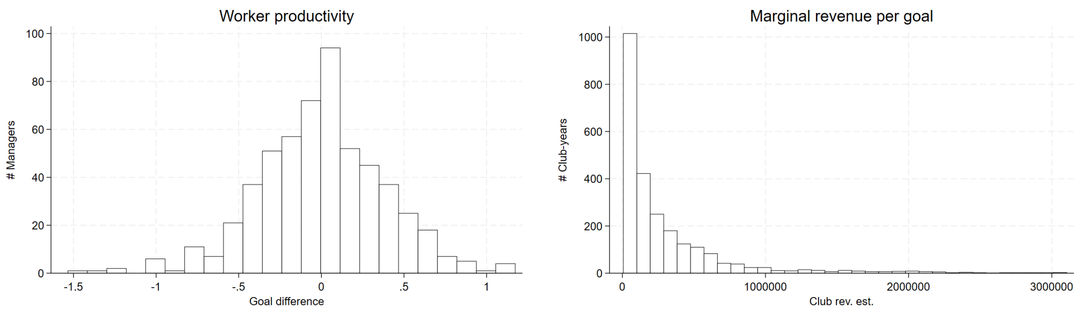
Note: Regression at club-year level. Standard errors in parentheses. *** significant at 1% level.

each club can achieve if it improves its on-field performance by 1 goal difference over the season, that is, $\frac{\partial R_{it}}{\partial y_{it}} = \beta R_{it}$. Note that, therefore, apart from the season, club and league effects, the asset level of the club also has an impact on the marginal revenues we calculate here.

In this analysis, we assume that the influence of the manager on the revenues of the firm works entirely through the performance on the pitch. For the vast majority of managers, this is reasonable as they are not 'superstars' who draw additional fan interest by themselves. In contrast, Scarfe et al. (2021) show that this channel may be present in football players. We return to this issue in the robustness checks.

In Table 3, we show the summary statistics by season and federation for the productivity estimates of workers and firms. The unit of measurement for worker productivity is added goal difference per game. We normalize the worker effects by the average worker in the entire sample, such that a positive or negative value should be interpreted as relative to the productivity of the mean worker. The overall average worker productivity measured at the level of the employment match is 0.052. This positive value indicates that workers with lower than average productivity estimates tend to have less employment matches, which is a first indication of selection on worker productivity. Over the seasons, we observe a slight upward trend in average worker productivity. This can be explained by lower productivity workers exiting from the labor market and being replaced by higher ability entrants. The average worker productivity by federation differs substantially from -0.324 in Scotland to 0.363 in Spain. Firm productivity is measured in 1000s of euros revenue per 1 added goal difference. The overall average stands at 326k. Also here we see an upward trend over time, which reflect the economic growth in the football industry over our sample period. The heterogeneity among federations is again substantial and appears to move along with the heterogeneity in worker productivity.

Figure 1: **Histogram Worker and Firm Productivity**



Note: Left panel: Histogram of worker productivity estimates based on model in Table 1. Observations at the worker level. Right panel: Histogram of marginal revenue of an additional goal difference calculated using the estimation results of Table 2. Observations are at the club-year level.

Figure 1 shows the distribution of the manager fixed effects in terms of their contribution to goal difference per match. The distribution is centered around 0 since all effects are scaled by the average worker effect. The bulk of the manager effects is located between -1 and +1. So, having a good manager from the top of the distribution creates around 1 more goals per game compared to the average, and up to 2 goals compared to a really bad manager. In the right panel of Figure 1 we show a histogram of the calculated marginal revenues. The marginal revenues are highly skewed, with a set of elite clubs outperforming the vast majority of clubs by a large margin.

5 Assortative Matching

In Table 3 we measure the degree of assortative matching by calculating the Spearman rank correlation, $\rho_S\left(\frac{\partial R_{it}}{\partial y_{it}}, \mu_m\right)$, between each firm's productivity rank and the productivity rank of the worker it employs. The rank correlation over all countries and seasons has a value of 0.460. In each of the individual year-by-year cross-sections the correlations are also uniformly positive and significant. This is clear evidence of positive assortative matching between workers and firms across national borders in the European football

Table 3: **Assortative matching between workers and firms**

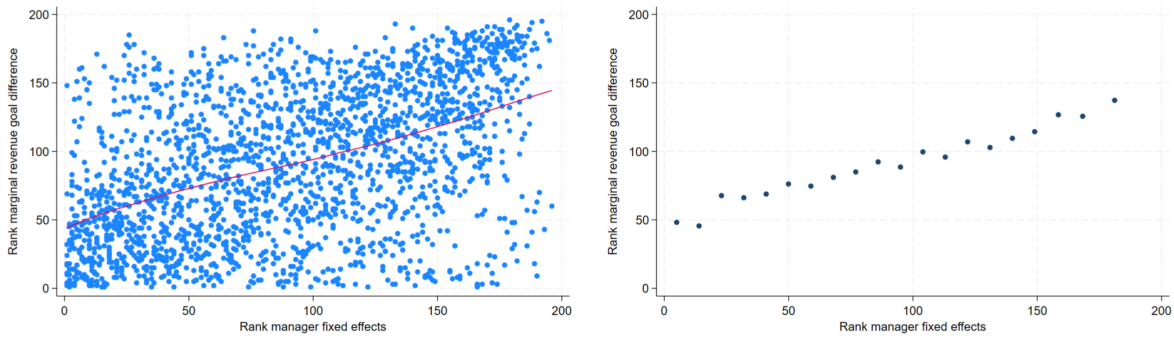
	Obs.	Worker productivity Mean	(Std. dev.)	Firm productivity Mean	(Std. dev.)	Spearman correlation Coef.	(S.E.)
Overall	2,150	0.052	(0.366)	326	(448)	0.460	(0.037)
Seasons							
2007-08	152	-0.002	(0.347)	258	(339)	0.330	(0.051)
2008-09	166	0.011	(0.382)	256	(317)	0.416	(0.056)
2009-10	174	0.001	(0.378)	272	(359)	0.557	(0.046)
2010-11	181	-0.026	(0.349)	260	(344)	0.565	(0.044)
2011-12	179	0.002	(0.354)	284	(394)	0.491	(0.047)
2012-13	183	0.005	(0.358)	281	(384)	0.393	(0.050)
2013-14	196	0.035	(0.354)	284	(391)	0.416	(0.046)
2014-15	191	0.049	(0.349)	318	(435)	0.391	(0.050)
2015-16	186	0.077	(0.337)	346	(460)	0.489	(0.049)
2016-17	190	0.114	(0.380)	394	(533)	0.499	(0.044)
2017-18	184	0.150	(0.370)	442	(584)	0.394	(0.055)
2018-19	168	0.197	(0.366)	507	(628)	0.517	(0.057)
Federations							
Belgium D1	131	-0.020	(0.404)	147	(102)	0.302	(0.085)
England D1+D2	482	0.035	(0.323)	455	(541)	0.571	(0.059)
France D1+D2	441	-0.023	(0.295)	192	(262)	0.535	(0.062)
Germany D1	120	0.069	(0.405)	751	(567)	0.229	(0.095)
Italy D1+D2	419	0.153	(0.273)	293	(343)	0.482	(0.065)
Netherlands D1	178	-0.212	(0.328)	156	(166)	0.480	(0.083)
Portugal D1	116	0.111	(0.455)	192	(256)	0.569	(0.077)
Scotland D1	53	-0.324	(0.547)	118	(141)	0.487	(0.085)
Spain D1	210	0.363	(0.311)	513	(688)	0.364	(0.092)

Note: Worker productivity is expressed in added goal difference per game. Firm productivity refers to 1000 euros per marginal unit of goal difference. Table reports the spearman rank correlation along with its standard error. Standard errors are bootstrapped by re-estimating the worker and firm productivity models 100 times in samples with replacement to construct a sampling distribution of the spearman rank correlation.

manager labor market. Moreover, there is little reason to conclude that the international labor market sees less assortative matching than each national market. The bottom panel of Table 3 shows the rank correlations within each federation over all seasons. These are also positive and significant. In itself, this should not be surprising as the differences in revenue productivity are enormous both within and across federations. For example, a highly productive manager working in the average Dutch or Belgian club can triple the revenue equivalent of his contribution to sporting output by moving to the average Spanish club.

To further illustrate the degree of assortative matching, Figure 2 shows a scatter plot over all yearly worker and firm rankings. Although the spread is large, there are fewer observations in the north-west and south-east part of the diagram. Furthermore, the locally estimated scatterplot smoothing line is clearly upward sloping. This is confirmed in a bin scatter plot of the same data in the right hand panel. The pattern emerging from

Figure 2: **Rank Correlation Worker and Firm Productivity**



Note: The rank correlation is based on estimates presented in Sections 4.1 and 4.2. The straight lines in the LHS graph represents the Locally Estimated Scatterplot Smoothing.

these graphs indicates a positive relationship between the relative ranking of a worker and firm in an employment match. The relationship is far from perfect as there are also managers with high fixed effects that match with low marginal revenue firms.

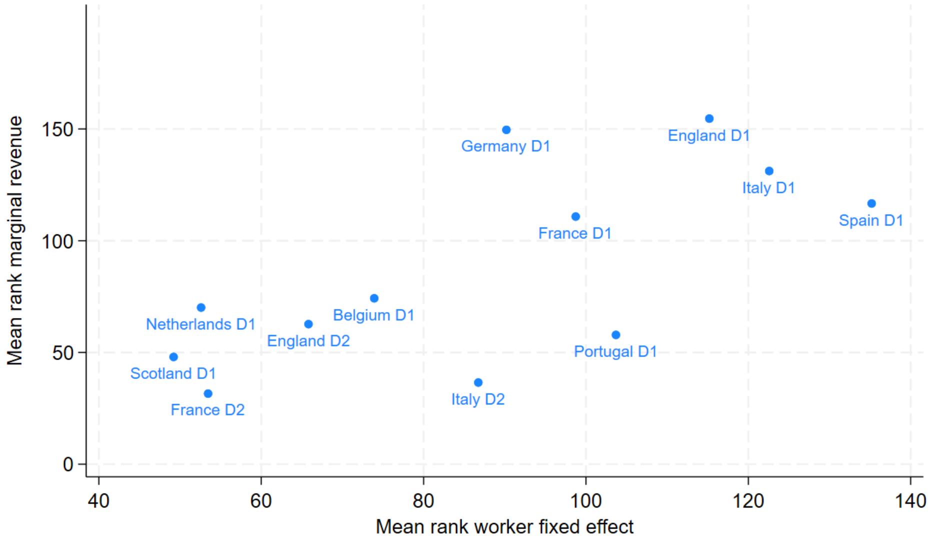
Figure 3 presents an overview of the productivity rankings of workers and firms averaged by country and division. The firms in the top leagues of England, Italy and Spain have on average the highest marginal revenue rank as well as the highest ranked workers. The top divisions of Belgium and the Netherlands are close to the second division of England both in terms of ranking of workers and ranking of firms. In this respect, the Scottish top division is close to the French second division. The graph underscores the heterogeneity in worker and firm productivity across countries, and we again observe a positive correlation between the worker and firm productivity rank. In other words, on average the most productive workers are employed in the most productive leagues.

6 Mobility of Workers

Two mechanisms may contribute to assortative matching in the labor market: highly productive workers may be employed by high productivity firms from the start of their career and/or high productivity workers may move from low productivity towards high productivity firms.

Table 4 gives an overview of worker mobility. The bottom row of the first three columns show that our sample consists of 2,150 observations of 297 firms (clubs) and 551 workers (managers). Of the 551 workers 78 are only observed once while for 473 workers

Figure 3: **Rank Correlation Worker and Firm Productivity by League**



Note: For all federations we show the average in the first division (D1); for England, France and Italy we also plot the average for the second division (D2).

we have multiple observations.[11]

Table 4: **Worker Mobility – Within and Between Countries**

Federations	Obs.	Firms	Workers	Obs./worker 1	> 1	Mobility No	Yes	Country Mobility Within	Between
Belgium (D1)	131	19	40	8	32	94	37	26	11
England (D1+D2)	482	55	107	16	91	350	132	104	28
France (D1+D2)	441	51	101	16	85	334	107	96	11
Germany (D1)	120	17	32	3	29	90	30	18	12
Italy (D1+D2)	419	64	111	16	95	243	176	162	14
Netherlands (D1)	178	24	49	4	45	125	53	35	18
Portugal (D1)	116	24	38	3	35	69	47	35	12
Scotland (D1)	53	9	12	0	12	43	10	6	4
Spain (D1)	210	34	61	12	49	137	73	52	21
Total	2,150	297	551	78	473	1485	665	534	131

Note: Obs. = Number of observations (worker-firm); Firms = Number of firms; Workers = Number of workers; Mobility = number of moves from firm to firm.

We have 1485 observations where workers stayed at the same firm. There were 534 moves to a different employer within the same country and 131 to a new employer in a different country (in our sample). So of all mobility movements in our sample about 20%

[11] Of the 297 employers 23 are observed only once. Note that the figures in Table 4 probably understate the extent of labor mobility in the labor market, as we exclude employment spells for which we are unable to estimate either worker or firm productivity.

is related to cross-country mobility. There are clear differences in worker mobility across countries. Whereas for managers in Italy and France only about 10% of the moves was to a different country this was about 40% in Germany and Scotland. The 131 moves to a different country involved 81 managers, corresponding to an average of 1.6 moves per manager. The moves were unevenly distributed across managers. There was one manager who moved internationally five times (Carlo Ancelotti), three managers moving internationally four times, five who moved three times, 27 who moved two times and 45 managers who moved once.

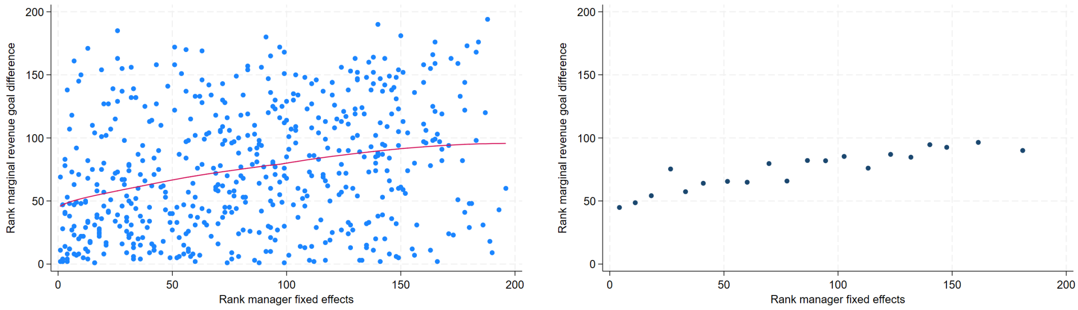
We first examine the assortativeness of the initial employment match for the 551 workers in our dataset. Figure 4 shows scatter plots of the worker vs firm productivity rankings similar to Figure 2. In the top graphs we restrict the sample to the first employment match of each worker in our dataset. We show a regular and a bin scatter plot. In both panels, we observe a positive correlation between the two rank indicators, i.e., there is positive assortative matching in the initial allocation of workers. The Spearman rank correlation in this sub-sample is 0.284. While this number is significant at the 0.1% level, it is lower than the overall correlation of 0.460 (see Table 3). This suggests that subsequent mobility of workers also plays a role in generating the level of international assortative matching we observe. Note that we may be understating the role of worker mobility as workers may either have moved before our sample period starts or their first employment spells may have been at clubs outside the scope of our dataset. The effect of these unobserved mobility events is absorbed by the initial allocation in this analysis.

The middle part of Figure 4 shows the scatter and bin scatter plot between the productivity ranking of workers who were mobile within a country and the productivity ranking of the firm they moved to. The positive relationship between the worker ranking and the destination firm productivity is clear. Highly productive workers are likely to move to more productive firms in the same country. The Spearman rank correlation for this sub-sample amounts to 0.397, which is also significantly different from 0.

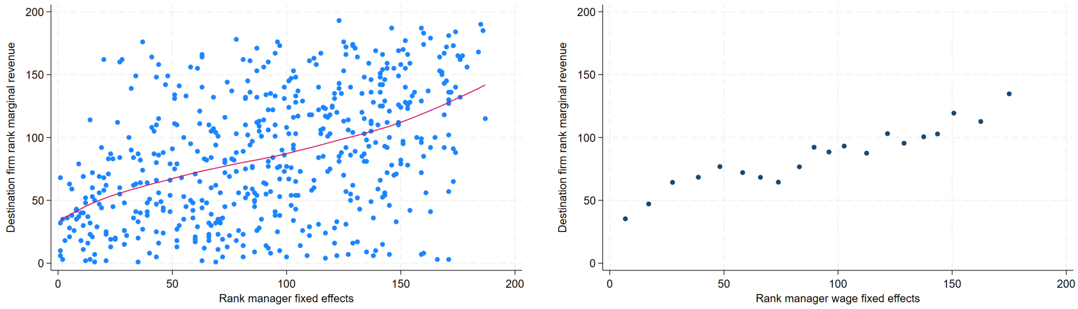
The bottom part of Figure 4 shows the scatter and bin scatter plot between the productivity ranking of workers who were mobile between countries and the productivity ranking of the firm they moved to. Here, the Spearman rank correlation is 0.522 suggesting stronger positive assortative matching between countries than within countries. In combination, Figure 4 implies that the positive assortative matching we observe is related to both the initial situation and job mobility within and between countries later

Figure 4: **Assortative Matching: Initial Allocation and Mobile Workers**

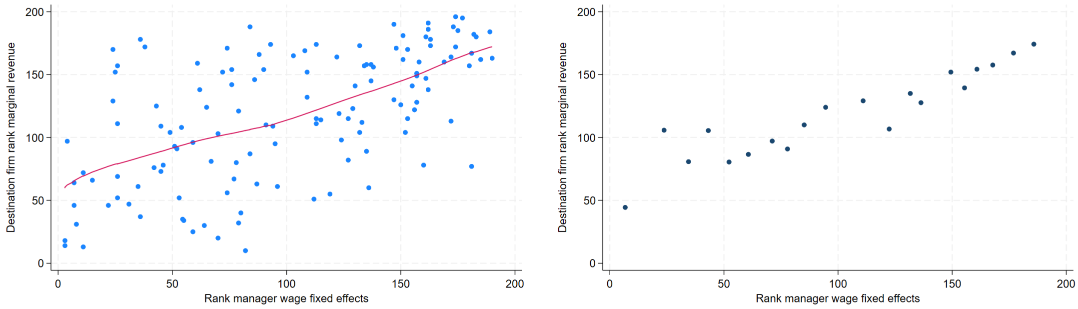
a. Initial Allocation



b. Within-country Mobility



c. Between-country Mobility



Note: Initial allocation is defined as the employment match in the first season in which we observe each of the 551 workers in our sample. There were 665 moves from firm to firm of which 534 were within countries and 131 were between countries. The productivity rank of the destination firms is calculated on the ex-post productivity of the new firm – i.e., the year after the move. The straight lines in the LHS graphs represent the Locally Estimated Scatterplot Smoothing.

on. There does not seem be an issue of borders between countries that would hinder job to job mobility.

We complement the visual evidence with some conditional correlations using regression analysis. We focus on the direction of mobility. In column (1) of Table 5 we show the parameter estimates of the regression of the logarithm of the marginal revenue estimate of the mobile worker's destination firm on the estimated productivity of the worker and his current firm.[12] In column (2) we add personal characteristics (age and migrant status) and in column (3) also year and country fixed effects to the model. The results clearly show that more productive workers ceteris paribus move towards more productive firms. Likewise, the productivity of the source firm is positively related to that of the destination firm. Adding personal characteristics and fixed effects does not affect these results. Being a migrant (defined relative to the source firm) has a positive effect on the productivity of the destination firm, but this result is not significant once country and year fixed effects are included. The effect of age is insignificant. We conclude that the mobility of workers in this labor market contributes to the emergence of assortative matching.

Table 5: **Regression Results Log Productivity Destination Firm**

	(1)	(2)	(3)
log(Productivity current firm)	0.529***	0.508***	0.444***
	(0.034)	(0.037)	(0.042)
Worker productivity	0.979***	0.984***	1.038***
	(0.105)	(0.106)	(0.116)
Migrant		0.159*	0.111
		(0.088)	(0.088)
Age		0.238	0.255
		(0.502)	(0.523)
Observations	665	665	665
R-squared	0.468	0.471	0.507
Country FE	No	No	Yes
Year FE	No	No	Yes

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

7 Sensitivity and Robustness

The main findings from our analysis are clear. We find positive assortative matching between workers and firms for which there are two main mechanisms: initial allocation and worker mobility. We also conclude that positive assortative matching occurs both within countries and between countries. In this section we investigate how robust our conclusions are.

[12] Fixed effects representing worker productivity are estimated using a different dataset. To the extent that unobserved worker ability is important this is picked up by these fixed effects.

7.1 Alternative sample selection

We first investigate how sensitive our main findings are with respect to the specific dataset we use. In our data selection process we omit observations of firms for which there is no information about their total wage bills. In Appendix A1, we do not use this criterion and estimate the worker effect without this control variable. As shown in Table A.1, the results line up closely with the main results presented in Table 3. Again, we find strong evidence of positive assortative matching within and across countries for all sample year.

Next, we relax the inclusion criterion for workers in the sample. In the main estimation of the worker fixed effects we require workers to be present in the sample for at least 35 games. In appendix A1, we show our main findings if we are lower the minimum number of games to 10 observations. Table A.1 shows that this does not change the overall correlations, but increases the bootstrapped standard errors. At the national level, all correlations remain positive, but we do not find a significant correlations in Scotland anymore.

Finally, we show how our results are affected by only using games from past seasons in the worker productivity estimates. We implement the estimation logic of Peeters et al. (2022) and Bhaskarabhatla et al. (2021), which only uses observations from past years in the worker productivity estimation. While this method leads to a severe restriction of the sample size, it hardly affects the correlations overall (see Table A.2). However, we lack observations in several countries to make firm conclusions at the national level.

7.2 Subsample analyses

We next examine the assortative matching in several sub-samples of the overall dataset, leaving out the smaller leagues and second divisions. As shown in Table B1, the main results are not affected by this. We still find significant positive assortative matching overall in both subsamples.

7.3 Workers' direct effects on revenues

As a final robustness analysis, we investigated to what extent the influence of a manager on firm revenues works only through the sporting results. If a new manager started at a club, the effect on revenues could work through the results but it is also possible that revenues increased beyond performance through high expectations of supporters or by attracting new supporters. For this, we re-analyzed the data on log annual revenues for the first season of a new manager at a club. In Appendix B2, we show that there is no additional effect of a new manager beyond the sporting results.

8 Conclusions

Our paper investigates assortative matching between high-productivity workers and high-productivity firms in a European context. We distinguish within-country from between-country matching of workers and firms. Our analysis is based on information from professional football, i.e., on the allocation of managers (workers) across clubs (firms) in nine European countries over a period of twelve years.

In our analysis we use two separate measures of productivity of workers and firms. The productivity of workers (managers) is related to sporting performance; the productivity of firms (clubs) is specified in terms of revenues conditional on sporting performance. The productivity of a worker is measured as his contribution to the sporting performance at the level of individual football matches. We measure this as the difference between goals scored and goals conceded. The productivity of a firm is measured at the seasonal level as the marginal revenues for the club of scoring across a season an additional goal or conceding one goal less.

We find a positive correlation between productivity of workers and firms within countries and at the international level. The average productivity of workers and firms varies strongly within and between countries. Mobility of the workers in our sample is positive assortative. High-productivity workers are more likely to make an upward move, i.e., to move to a firm with a higher productivity. We also find that the initial allocation of the workers in our sample is positive assortative: from the start of the observation period more productive workers are at more productive firms. Of course, the initial allocation in our sample is likely to have been the result of earlier job mobility. In this sense (cross-border) mobility facilitates international assortative matching.

What do we derive from the results of our empirical analysis? Our main conclusion is that in the labor market we study there is positive assortative matching with country borders not being particularly restrictive. The assortative matching within countries occurs similar to the assortative matching across countries as if borders are non-existent. Cross-border mobility is driven by better workers moving to more productive firms. At the high end good matches between workers and firms are more important than country borders.

Is the labor market of professional football managers a good example of how a high-skilled labor market typically operates? In most settings, it is not possible to separate physical output from monetary output, which we use to identify assortative matching in our setting. We accept that the market for football managers differs from many other markets in this aspect. Due to popular media attention, the labor market we study is characterized by easily observable productivity of both workers and firms. The market is also homogeneous in the sense that workers have about the same tasks and firms have about the same production process in different countries. Further characteristics include high wages, a largely common language to communicate and transparency in how firms operate. However, these characteristics are not unique. There are similar labor markets of high-productivity workers with different qualifications like university academics where the production process (teaching and research) is similar across borders or entertainers and top executives of regular firms where the production processes may be firm-specific but managing these firms in terms of decision-making and accountability implies that there are big similarities with the labor market of football managers. Therefore, our main findings are not only relevant for the labor market of international professional football managers but indicative for other high profile labor markets.

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Appendix A: Alternative sample selection

A1: Results with extended samples

In Table A.1 we repeat our analysis of assortative matching using two alternative samples.

In the "no wage control" sample we do not include the firm wage bill in the estimation of worker productivity. Because of this, the sample size in the matching analysis increases from 2,150 to 2,229 observations. The overall correlation slightly increases. We find very similar patterns across years and associations. All correlations remain highly significant and clearly positive.

In the ">10 obs." sample we lower the requirement to include a worker from 35 observations to 10 observations. The number of observations further increases to 2,380 overall. The estimated correlations are similar to the main sample analysis, both overall and across years. The standard errors increase, presumably because the worker effects are estimated with larger uncertainty. Looking at the correlations by country, we see that in this sample the correlation in Scotland is no longer significantly different from 0. For all other countries, our conclusions are confirmed.

Table A.1: **Assortative Matching in Extended Samples**

	Main sample			No wage control			>10 obs.		
	Obs.	Spearman	(S.E.)	Obs.	Spearman	(S.E.)	Obs.	Spearman	(S.E.)
Overall	2,150	0.460	(0.037)	2,229	0.530	(0.029)	2,380	0.493	(0.081)
Seasons									
2007-08	152	0.330	(0.051)	158	0.385	(0.046)	180	0.353	(0.096)
2008-09	166	0.416	(0.056)	171	0.481	(0.037)	186	0.428	(0.094)
2009-10	174	0.557	(0.046)	181	0.622	(0.034)	191	0.579	(0.101)
2010-11	181	0.565	(0.044)	188	0.589	(0.043)	197	0.556	(0.085)
2011-12	179	0.491	(0.047)	186	0.588	(0.034)	199	0.519	(0.072)
2012-13	183	0.393	(0.050)	191	0.509	(0.042)	198	0.430	(0.081)
2013-14	196	0.416	(0.046)	205	0.510	(0.039)	209	0.458	(0.089)
2014-15	191	0.391	(0.050)	198	0.477	(0.046)	208	0.455	(0.081)
2015-16	186	0.489	(0.049)	191	0.517	(0.042)	203	0.523	(0.085)
2016-17	190	0.499	(0.044)	193	0.538	(0.040)	207	0.517	(0.092)
2017-18	184	0.394	(0.055)	193	0.474	(0.048)	205	0.487	(0.105)
2018-19	168	0.517	(0.057)	174	0.618	(0.043)	197	0.560	(0.106)
Federations									
Belgium D1	131	0.302	(0.085)	131	0.324	(0.090)	141	0.354	(0.098)
England D1+D2	482	0.571	(0.059)	486	0.629	(0.049)	505	0.570	(0.115)
France D1+D2	441	0.535	(0.062)	441	0.595	(0.055)	465	0.509	(0.119)
Germany D1	120	0.229	(0.095)	132	0.241	(0.083)	136	0.224	(0.101)
Italy D1+D2	419	0.482	(0.065)	430	0.497	(0.055)	456	0.493	(0.076)
Netherlands D1	178	0.480	(0.083)	188	0.574	(0.074)	208	0.563	(0.136)
Portugal D1	116	0.569	(0.077)	126	0.579	(0.073)	139	0.597	(0.128)
Scotland D1	53	0.487	(0.085)	84	0.397	(0.115)	99	0.078	(0.138)
Spain D1	210	0.364	(0.092)	211	0.409	(0.073)	231	0.403	(0.072)

Note: Table reports the spearman rank correlation along with its standard error. Standard errors are bootstrapped by re-estimating the worker and firm productivity models 100 times in samples with replacement to construct a sampling distribution of the spearman rank correlation.

A2: Prior games estimation sample

In Table A.2 we report results on assortative matching where we estimate worker productivity using a similar estimation algorithm to Peeters et al. (2022) and Bhaskarabhatla et al. (2021). This algorithm excludes observations from games played in seasons during and after the employment match under analysis. For example, to establish the ranking of worker productivity at the start of the 2018-19 season, we do not consider games played in the final season of the data. For employment matches at the start of the 2017-18 season, we disregard all games played in the two final seasons etc. As such, we use a 'prior games' estimation sample to establish year-by-year estimates of worker productivity. This methodology prevents that worker estimates are contaminated by performance after the employment match, which could not have affected the decision making of the hiring firm.

Table A.2: **Assortative Matching Prior Games Sample**

		Worker productivity		Firm productivity		Spearman correlation	
	Obs.	Mean	(Std. dev.)	Mean	(Std. dev.)	Coef.	Sign.
Overall	418	0.181	(0.431)	484	(613)	0.465	0.000
Seasons							
2016-17	133	0.164	(0.379)	424	(542)	0.401	0.000
2017-18	142	0.169	(0.382)	488	(618)	0.530	0.000
2018-19	143	0.210	(0.395)	535	(666)	0.447	0.000

Note: Worker productivity estimates are based on a rolling window sample which cuts the game data at the final game of the season preceding the observed worker-firm employment match. Worker productivity is expressed in added goal difference per game. Firm productivity refers to 1000 euros per marginal unit of goal difference.

To allow a clear comparison with the results in the main paper, we keep all other modeling choices constant to our main specification. We require 35 game observations and a connected network for identification of the worker effects. Note that these 'fixed' effects are updated year-by-year. We therefore demean them by the average estimated effect for the year under consideration. All assumptions underlying the marginal revenue ranking are unchanged. These sample selection requirements are quite stringent and do not allow to estimate worker productivity to rank a critical number of workers in the first years in our data sample. Hence, we only use the last three seasons for this analysis.

In the top panel of Table A.2 we show the results aggregated over the three final years and by year. The means of both the worker productivity and firm marginal revenue estimates are above the main sample mean reported in Table 2. This is the result of selecting the final sample years, as both are on an increasing trend over time. For assortative matching, we find Spearman correlations between 0.401 and 0.530, which aligns closely with our main findings.

Appendix B: Additional sensitivity analyses

B1: Subsample analyses

To supplement our analysis of assortative matching, we perform two further robustness checks. First, we show the rank correlations if we remove federations for which we have fewer observations (Belgium, Germany, Portugal, and Scotland) from the sample. Table B.1 shows that the rank correlation in the remaining observations increases somewhat but is not very different from the rank correlation in the overall sample.

Next we separate the first division clubs from the second division clubs. The rank correlation in the top divisions is again broadly similar to the overall sample.

Table B.1: **Assortative Matching Selected Sub-samples**

		Worker productivity		Firm productivity		Spearman correlation	
	Obs.	Mean	(Std. dev.)	Mean	(Std. dev.)	Coef.	(S.E.).
Main sample	2,150	0.048	(0.366)	326	(448)	0.461	(0.037)
No small federations	1,729	0.060	(0.339)	325	(452)	0.534	(0.036)
First division	1,497	0.109	(0.378)	436	(498)	0.425	(0.051)

Note: Worker productivity is expressed in added goal difference per game. Firm productivity refers to 1000 euros per marginal unit of goal difference. Table shows bootstrapped standard errors for the spearman rank correlations based on 100 iterations.

B2. Workers effects and future revenues

If a new manager starts at a club, the effect on revenues could work through the sportive results but it is also possible that revenues increased beyond performance. To investigate this, we re-analyzed the data on log annual revenues for the first season of a new manager at a club. Appendix Table B.2 presents three sets of parameter estimates. The first column replicates the analysis in Table 2 for the 665 managers who started working at a new club. The magnitude of the parameter estimates differs somewhat but the general pattern is very similar. In the second column we add manager fixed effects. These do not have a significant effect on log annual revenues. In the third column we omit goal difference. In this case the manager fixed effects are highly significant. From this, we conclude that the effect of a new manager works through the sporting results.

Table B.2: **Extended Regression Results Log Annual Revenues**

	(1)		(2)		(3)	
Goal difference	0.154***	(0.034)	0.145***	(0.037)		
Log Tang. assets	0.065***	(0.015)	0.066***	(0.015)	0.070***	(0.015)
Promoted	-0.154***	(0.045)	-0.152**	(0.045)	-0.147**	(0.046)
Relegated	0.409***	(0.066)	0.409***	(0.066)	0.424***	(0.067)
Manager effects			0.034	(0.057)	0.127**	(0.052)
Firm FE	Included		Included		Included	
League FE	Included		Included		Included	
Year FE	Included		Included		Included	
R-squared	0.972		0.972		0.971	

Note: 665 observations of mobile workers; fixed effects for club, season and league-division are included; standard errors in parentheses. *** significant at 1% level, ** significant at 5% level.