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International Assortative Matching in the European Labor Market

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Abstract

We investigate whether national borders within Europe hinder the assortative matching of workers to firms in a high skilled labor market. We characterize worker productivity as the ability to contribute to physical output and define firm productivity as the capacity to transform physical output into revenues. We rank workers and firms according to their individual productivity estimates and study the ensuing rank correlation to gauge the degree of assortative matching within and across countries. We find strong evidence for positive assortative matching at the national level, and even more so at the international level. This suggests national borders do not prevent workers and firm from pursuing profitable complementarities in production.

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 initially recruit. This process leads to 'positive assortative matching' between workers and firms in labor market equilibrium. If 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)). In this paper we investigate whether national borders within Europe create market frictions, which hinder the cross-border assortative matching of workers to firms in high-skilled labor markets.

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 reform in the Swiss labor market 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 skill 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. On the one hand, this increased surplus may help workers overcome the hurdles inherent in international migration. On the other hand, the implied efficiency loss if they would not overcome them, could be particularly severe.

To shed light on this question, we analyse the strength and direction of assortative matching in the European labor market for football managers[1]. Our data tracks around 700 managers (workers) employed by over 300 clubs (firms) across nine European countries. We exploit the fact that we directly observe physical output (sporting results) in our setting to establish independent productivity rankings of workers and firms. We measure worker productivity as the ability to generate physical output from inputs (player wages) and gauge firm productivity by the amount of revenues firms generate from a given amount of physical output. We then examine the correlation between these rankings at the national level, i.e., among firms and workers within the same country, and across all countries in the data, i.e., in the international European labor market. We find substantial positive correlations between the productivity indicators of workers and firms both at national and international level. The positive matching at international level is even stronger if we consider workers that moved cross-country. We interpret this as clear evidence for positive international assortative matching. The match surplus created in this European labor market is large enough to overcome the frictions imposed by national borders.

The rest of our paper is set-up as follows. First, we sketch the literature on assortative matching in the labor market and describe how our setting allows us to identify the degree of assortative matching. In section 3, we present the structure and summary statistics of our data. After setting out the general structure of our analysis in section 4, we establish a ranking of workers by their estimated ability in section 5, followed by the ranking of firms by marginal revenue product in section 6. After this, section 7 lays out our findings on the degree of assortative matching between workers and firms. Section 8 concludes.

[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.

2 Related Literature and Setting

2.1 Assortative Matching Literature

Despite its prevalence in theoretical models and intuitive appeal, it has proved challenging to confirm the presence of positive assortative matching 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. 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. (2022)). One 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 bias in the correlation between both constructs. In real-life data samples, the worker effects suffer from measurement error. As workers have typically been employed by a small number of firms and firms do not have an infinite amount of workers, these errors in the worker effects disturb the estimation of the firm effects in a non-random way. Simply put, when the worker effects at a firm are relatively 'overestimated', the firm effect will be relatively 'underestimated' and vice versa. This effect is more pronounced when there are fewer observations per worker and fewer mobile workers linking the firm to other firms in the data, hence the term 'limited mobility bias' (Andrews et al. (2008), Jochmans and Weidner (2019)).

In response, researchers looked for other methods to gauge the degree of assortative matching. Both 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 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. Other authors look 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.

A final approach to circumvent empirical issues in establishing assortative matching is to leverage data from professional sports where researchers can directly observe the performance of individual athletes and teams of athletes to form worker ability rankings. Gandelman (2008) analyzes Uruguayan football data ranking clubs according to points and prizes achieved and ranking players using newspaper journalist' evaluations of performance. He finds that high performing players are more likely to move to high performing teams suggesting that there is positive assortative matching. Filippin and van Ours (2015) exploit panel data on running performance of individuals and their teams participating in a 24-hour relay marathon. They find that runners who over-perform relative to their team average are more likely to quit for better teams, i.e., there is positive assortative matching.[2]

2.2 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

[2]Both Drut and Duhautois (2017) and Scarfe et al. (2020) estimate worker and firm effects along the traditional approach using wage data from the Italian and US football leagues, respectively. They find contradicting results with a positive correlation between worker and firm effects for Italy, but a negative correlation for the US. Drut and Duhautois (2017) show that when dropping movers from their sample the positive correlation between the two types of fixed effects drops and eventually becomes negative. Thus, they confirm the limited mobility sample bias inducing a negative correlation (Andrews et al. (2008)).

of the club's players on the pitch. To achieve this, professional football managers perform typical middle management functions such as motivating the team, resolving conflicts between players, selecting the game line-up and developing training routines. In some cases, managers will 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. Based on this, our approach to measuring assortative matching is to (a) rank managers by their estimated ability to transform the club's inputs (mainly investments in playing talent) into sporting performance, (b) rank firms by their capability to generate revenues from the team's sporting performance and (c) examine the correlation between these rankings.

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.[3] 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)) and poach over-performing managers from rival firms (Peeters et al. (2022)).

Second, at each point in time a club employs only one manager who has overall responsibility. Likewise, vacancies are filled quickly such that the tenure of interim workers (or 'caretaker' managers) is typically no more than a couple of weeks. This means we can clearly ascribe the performance of the team to a specific worker. In most linked employer-employee data sets, it is also difficult measure the correlation between a firm's productivity ranking and that of its workers, because each firm typically contains many workers. We do not encounter this problem here.

[3]For example, Muehlheusser et al. (2018) leverage this public information to estimate the heterogeneity in managerial ability in the Bundesliga.

Third, football managers experience a lot of job turnover and typically work for multiple clubs during their career. This mobility creates the variation we exploit to separate the ability of managers to improve sporting performance from the capability of their employers to transform sporting performance into revenues. Furthermore, we directly observe the 'intermediate' output (sporting performance) produced at each of the manager's employers, such that we do not rely on information about manager wages to gauge assortative matching.

Finally, the social costs of moving from one European country to another may be less high for football managers than for many other professionals. For example, for an average worker's 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. Famously, 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.

3 Data

Our data set consists in two parts, one at the level of individual games, the other at club-season level. We use the game-level data to derive a ranking of managers and use the club-season data to derive a ranking of clubs. Our data cover the period 2000 to 2018, with the UEFA competitions (Europa and Champions League)[4], England, Scotland, and Spain entering from the start, followed by Italy from 2002, France from 2003, the Netherlands from 2005, Germany from 2007 and finally Portugal and Belgium from 2008. We include the highest professional tier for all countries, and the second divisions of England, France and Italy.

3.1 Game Level Data

We start our empirical analysis by collecting performance data at the game level. Clubs typically play one regular season game per week. Over the course of a season all clubs play each other twice, once at each club's home stadium. The structure of the UEFA tournaments is more complex and has varied over time. For each game we know the results in terms of goal difference and the identity of the manager for both clubs. In the analysis we also use the clubs' seasonal wage bill as a control variable. This is only possible when the financial statements contain this information. In order to avoid imprecise estimates of managerial performance, we focus our analysis on managers who appeared at least 35 times in the data and hence managed at least 35 games. It is only possible to identify worker effects a la Abowd et al. (1999) for workers belonging to the same 'network' of employers connected by moving workers, because the estimation requires a common benchmark worker and firm. We therefore identify the largest connected network in the data set and only keep games where the managers of both teams belong to this

[4]These competitions pitch clubs from different countries against one another.

network. This in turn may lead the number of observations of some managers to drop below 35, so we re-evaluate the presence of each manager after this step. We iterate this until we arrive at a stable network in which all managers have 35 game observations. After this selection procedure, the remaining sample holds 49,124 game observations with 678 managers and 316 clubs. [5] Table 1 provides game level summary statistics by country and division.

Table 1: **Game level information**

	Time period	Goals scored Home	Away	Δ	Wage bill	Obs.
First division						
Belgium	2008-2018	1.63	1.19	0.44	12.3	2,608
England	2000-2018	1.51	1.12	0.39	85.6	5,880
France	2003-2018	1.40	1.00	0.40	40.6	5,225
Germany	2007-2018	1.74	1.21	0.53	72.0	862
Italy	2002-2018	1.50	1.12	0.38	56.5	5,450
Netherlands	2005-2018	1.77	1.29	0.48	14.9	3,066
Portugal	2008-2018	1.49	1.10	0.39	17.7	1,049
Scotland	2000-2018	1.58	1.19	0.39	15.1	1,564
Spain	2000-2018	1.58	1.13	0.45	50.0	5,555
Second division						
England	2000-2018	1.45	1.11	0.34	21.1	7,582
France	2003-2018	1.36	0.95	0.41	8.0	4,548
Italy	2002-2018	1.39	1.02	0.37	10.1	4,334
Europe						
Champions League	2000-2018	1.55	1.12	0.43	139.0	813
Europa League	2001-2018	1.55	1.02	0.53	57.4	588
Total		1.50	1.10	0.40	38.1	49,124

Note: Averages calculated on the games in our sample. Average wage bill in million euro, Obs. = number of observations (games).

Football games have a clear home advantage in terms of goal difference.[6] As shown in the bottom row of Table 1 the home team scores an average of 1.50 goals

[5] Appendix A provides details on how each selection rule influences the number of observations

[6] See Peeters and van Ours (2021) for developments in home advantage in the English professional football leagues.

per game in our sample while the away team scores 1.10 goals per game. The home advantage is present in all countries and divisions, varying from 0.34 goal difference in the English second division to 0.53 goals in Germany and the Europa League. The highest average home team score is 1.77 goals (Dutch 1st division), the lowest average away team score is 1.36 goals (French second division).

Table 1 also shows that the overall average seasonal wage bill is 38.1 million euro. The average wage is highest in Champions League games, which is unsurprising as this format combines the top clubs from each national league. At the national level, the richest clubs are in the English first division with an average wage bill of 85.6 million euro. Second place are German first division teams with an average annual wage bill of 72 million euro. Even the second division English teams on average pay higher wages than the first division teams in Belgium, Netherlands, Portugal and Scotland.

3.2 Club-Season Data

Table 2 provides summary statistics of our season-level data. The sample consists of 3,016 observations. We again notice that there are huge differences in the financial situation of clubs. The overall average revenue in our sample is 63 million euro, but for individual clubs, the range is from 1.4 million to 897 million. These annual revenues include profits on player transfers.[7] Tangible assets also show a huge range as some clubs report no tangible assets whereas the maximum is over 1 billion euro. The differences in sporting performance are also huge. For individual clubs, the average goal difference per match ranges from -1.82 to +2.53. Over a season, the aggregate goal difference in a league is by definition equal to zero. We find an overall positive average (of 0.04) because we select on the availability of financial accounts. In our sample, 5% of the clubs have been relegated and 12% of the clubs are promoted. The share of promoted teams is higher because by definition there are no relegated teams in the top division.

[7] See Hoey et al. (2021) for a detailed discussion of the revenues clubs earn in the player transfer market.

Table 2: **Season-level information**

	Time period	Revenues	Tangible assets	Goal diff.	Previous season Relegated	Previous season Promoted	Obs.
First division							
Belgium	2008-2018	27.4	8.9	0.12	0.00	0.06	130
England	2000-2018	158.0	112.1	0.01	0.00	0.15	377
France	2003-2018	70.6	13.3	-0.02	0.00	0.16	290
Germany	2006-2018	145.5	63.3	0.07	0.00	0.11	140
Italy	2002-2018	97.9	9.9	0.02	0.00	0.16	323
Netherlands	2003-2018	30.8	9.5	0.10	0.00	0.07	241
Portugal	2004-2018	33.7	24.1	0.15	0.00	0.06	150
Scotland	2000-2018	22.5	29.6	0.10	0.00	0.05	174
Spain	2003-2018	144.1	64.2	0.10	0.00	0.14	142
Second division							
England	2000-2018	26.3	27.8	0.02	0.13	0.09	428
France	2003-2018	11.8	2.9	0.01	0.13	0.13	312
Italy	2002-2018	15.6	1.5	0.04	0.14	0.18	309
Total		63.0	30.8	0.04	0.05	0.12	3016

Note: Revenues and tangible assets in million euro; goal difference per match, relegated and promoted end of previous season, Obs. = number of observations (firm-seasons).

Clearly, there are also big differences between countries and by division. Average seasonal revenues in the first divisions in England, Germany and Spain are close to 150 million euro. In the second division in France the average seasonal revenue is about 12 million euro, in the second division in Italy this is about 16 million and in the first division in Scotland it is about 22 million. Tangible assets are more than 100 million in the first division in England and less than 2 million in the second division in Italy.

3.3 Mobility of Managers

Table 3 gives an overview of the mobility of football managers between clubs within a country and moves of managers from one country to another country (both countries being part of our sample). Our sample contains 316 unique clubs spread over 9 countries. These clubs collectively employ 678 managers.

Panel a of Table 3 presents the number of moves between clubs which totals

1428. The number of moves on the diagonal is substantial meaning that most of the manager moves are between clubs in the same country. The highest numbers of within country moves are for Italy (394), England (254) and France (185). The highest numbers of moves between country are from England to Scotland (21) and vice versa (18). The number of moves to England is also high from Italy (15) and Spain (12). Other high numbers are from the Netherlands to Belgium (13), from Belgium to the Netherlands (10), From England to Italy (11) and from Italy to Spain (10). There are also quite a few country pairs that do not have any mobility of managers between clubs. In particular mobility of managers to and from Germany and to and from Portugal is rather low.

Table 3: **Mobility of managers within and between countries**

a. Mobility between clubs; number of moves

To	From Bel	Eng	Fra	Ger	Ita	Net	Por	Sco	Spa	Total	Total in
Belgium	62	6	4	1	0	13	1	2	2	91	29
England	6	254	7	8	15	6	4	18	12	330	76
France	3	8	185	1	4	0	2	1	7	211	26
Germany	0	2	0	26	0	8	0	0	3	39	13
Italy	0	11	3	0	394	1	0	0	5	414	20
Netherlands	10	3	0	4	0	55	1	1	3	77	22
Portugal	1	0	1	0	0	0	48	1	4	55	7
Scotland	0	21	1	0	0	0	1	22	0	45	23
Spain	2	8	3	0	11	1	5	0	136	166	30
Total	84	313	204	40	424	84	62	45	172	1428	
Total out	22	59	19	14	30	29	14	23	36		

b. Mobility between clubs by manager

	Manager	Moves	Frequency
Within country	391	1182	3.02
Between countries	133	246	1.85
Mobile	524	1428	2.73
Not mobile	154		
Total	678		

Panel b of Table 3 shows mobility between clubs by manager. Of our sample of 678 managers, 524 changed clubs and 154 did not change clubs over our period of analysis. Of the 1428 moves, 1182 (83%) were within country. Within a country mobile managers on average made 3.02 moves between clubs while between countries managers who moved on average changed clubs 1.85 times. Moves between clubs and countries are crucial for the identification of the manager and club fixed effects. Table 2 shows that there is frequent mobility of managers between clubs not only within countries but also between countries. Clearly, there is an integrated international network of managers and clubs.[8]

4 Set-up Empirical Analysis

Our empirical analysis consists of three consecutive parts:

1. Using the game level data we estimate a model with goal difference y as dependent variable: $y = f(X, \gamma, \mu)$, where X represents home advantage and wages paid during a season, γ is a vector of team fixed effects and μ is a vector of manager fixed effects. Our ranking of worker ability is based on the manager fixed effect derived from this equation.

2. Using the seasonal data we estimate a relationship with firm revenues R as dependent variable: $R = g(y, Z, \alpha)$, where y represents the end-of-season goal difference, Z represents the value of tangible assets and α is a vector of firm fixed effects. From this equation, we calculate the firm's marginal revenue from additional sporting performance, i.e., the revenue obtained from one additional goal difference. We rank firms by this measure.

3. We investigate assortative matching by analyzing the rank correlation between the ranking of the manager effect μ and the marginal revenues of the firm related to one goal difference.

Our approach is clearly different from the traditional approach which measures assortative matching by the correlation between γ and μ. Using rankings based

[8] In Appendix B we formally analyze the connectedness of the worker-firm network in our sample based on the work of Jochmans and Weidner (2019). The results of this analysis are reassuring for the interpretation of our estimated effects.

on two independent models, allows us to avoid the spurious negative correlation which may exist between both fixed effects, when they are derived from the same regression model (see Andrews et al. (2008), Drut and Duhautois (2017)).

5 Estimating Worker Ability

Since the performance of workers in the labor market can readily be observed through the results of games, we do not rely on wage data to assess a worker's individual output productivity. Based on the measures developed in Peeters et al. (2022), we measure the productivity of a manager by his capacity to maximize the performance of the team on the field given the amount of playing talent, which the team 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 model the goal difference y_{gijlt} at the end of game g between two teams i and j played in league l in season t as follows:

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

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 their annual payroll expenditure. 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 of the firms and workers to the 'output' production. These worker fixed effects therefore serve as the primary measure of worker productivity in the empirical analysis.

As shown by Abowd et al. (1999), both the 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. The model presented in equation

(1) can then be estimated using simple linear estimation techniques. Through our data cleaning procedure we selected the largest network 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, or simply put, home advantage is the same for all managers. In the estimation of equation (1) use every game twice, once from the perspective of the home team and once from the perspective of the away team. In this way we can identify the home advantage parameter as a simple indicator variable and the home and away manager effects are equal for each manager by construction.

Table 4: **Parameter estimates analysis game-level data**

Dep.Var.: Goal dif.	Home advantage		Log wage	
1^{st} **division**				
Belgium	0.44***	(0.03)	0.68***	(0.15)
England	0.39***	(0.02)	0.58***	(0.08)
France	0.40***	(0.02)	0.64***	(0.07)
Germany	0.51***	(0.06)	0.68***	(0.17)
Italy	0.38***	(0.02)	0.44***	(0.05)
Netherlands	0.48***	(0.03)	0.26*	(0.15)
Portugal	0.37***	(0.05)	0.38***	(0.10)
Scotland	0.38***	(0.04)	0.62***	(0.19)
Spain	0.45***	(0.02)	0.36***	(0.06)
2^{nd} **division**				
England	0.34***	(0.02)	0.40***	(0.05)
France	0.41***	(0.02)	0.27***	(0.08)
Italy	0.37***	(0.02)	0.27***	(0.06)
European cups	0.48***	(0.04)	0.46***	(0.07)
Explained variance				
Manager fixed effects	$\frac{Cov(y,\mu)}{Var(y)}$	0.054		
Team fixed effects	$\frac{Cov(y,\gamma)}{Var(y)}$	0.029		
Time-varying covariates	$\frac{Cov(y,X)}{Var(y)}$	0.140		
R-squared		0.223		

Note: 98,248 observations (every game is included twice in the regression) of 678 mangers and 316 teams; standard errors in parentheses *** significant at 1% level, * significant at 10% level.

We summarize the main estimation results of our game-level analysis in Table 4. The home advantage is highly significant in every country and division and also in European-level competitions. The range of the home advantage effect is limited from a low 0.34 goals in the second division in England to a high 0.51 goals in the top German division. The effect of the (log) wage sum is also significant in every league and division although there are clear differences. The parameter estimate for the first division in the Netherlands is only significant at a 10% level. Both manager fixed effects and club fixed effects contribute a lot to the explained variance in the goal differences. Almost two-thirds of the explained variance comes from the time varying variables, the wage bill and home advantage. This is not at all surprising since teams with larger wage bills on average are able to attract better players. Nevertheless, money is not everything as there is also a substantial contribution of the fixed effects of the clubs (10-13%) and an even larger contribution of the fixed effects of the managers (24-25%).

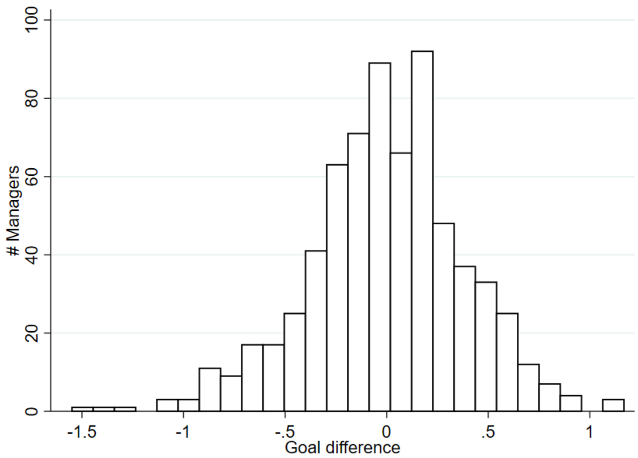
The results presented in Table 4 imply that the production of the team in terms of goal difference is determined to a large extent by psychological (home advantage) and economic (wages paid) factors. In addition to that, the productivity of the worker is clearly important. Some managers are able to derive better results in similar circumstances. It is the manager who determines the composition of the team, playing tactics and substitution of players during the match. The nature of the team fixed effects may refer to the scouting operation or youth development program of the club. These 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 effect further in our main analyses.[9]

Figure 1 provides a graphical representation of the distribution of the manager fixed effects in terms of their contribution to goal difference per match. As we scale all effects by the average worker effect, the distribution is centered around 0. The bulk of the manager effects is located between -1 and +1 in terms of goal difference.

[9]By way of sensitivity analysis, we also calculate the correlation between the estimated manager and club fixed effects from equation (1). This analysis replicates the traditional (potentially biased) approach to assortative matching. See Appendix C for results.

This implies that 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 when compared to a really bad manager.

Figure 1: **Histogram worker fixed effects**



Based on parameter estimates for 678 managers presented in Table 4

6 Estimating Firms' Marginal Revenues

We now estimate each firm's revenue productivity, which we define as the marginal revenue increase of an improvement in on-field performance. In doing so, we assume that the relationship between revenues and goal scoring is not directly affected by the manager. The influence of the manager on the revenues of the firm works entirely through the performance on the pitch. We model the revenues R_{lit} using a log-linear specification similar to the one used in Peeters and Szymanski (2014):

$$R_{ilt} = \beta_l y_{it} + \beta_x Z_{it} + \alpha_i + \tau_t + \lambda_l + \epsilon_{ilt} \tag{2}$$

In equation (2), y_{it} stands for the on-field performance of team i in year t, measured by the end-of-season 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 main parameter estimates of equation (2) are presented in Table 5. We show three different sets of parameter estimates, with and without tangible assets and with and without indicators for recent promotion and relegation. The parameter estimates are quite stable. Performance on the field has a significant positive effect on (log) revenues. 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.

Table 5: **Parameter estimates (log) revenues model**

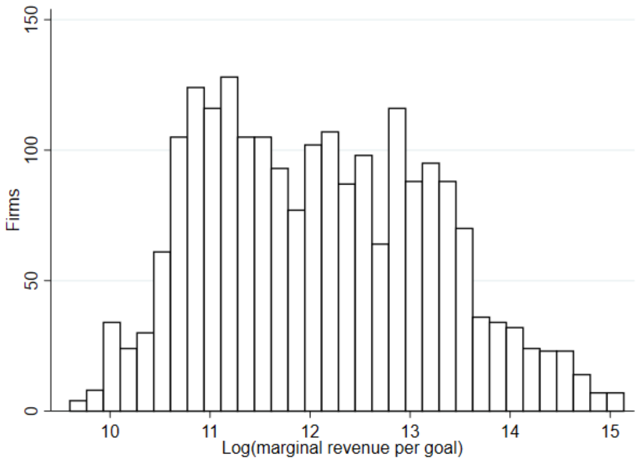
Goal difference	0.204***	(0.015)	0.203***	(0.014)	0.191***	(0.014)
Tang. assets	0.068***	(0.006)			0.057***	
Promoted			-0.113***	(0.018)	-0.093***	(0.018)
Relegated			0.465***	(0.028)	0.442***	(0.027)
R-squared	0.945		0.949		0.951	

Note: Based on 3,016 observations of 316 firms. All estimates include fixed effects for club, league, country and season; standard errors in parentheses. *** significant at 1% level.

Using the estimates in Table 5 we calculate the additional revenues each club can achieve if it improves its on-field performance by 1 goal difference over the season. Note that 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. Figure 2 shows the distribution of the marginal revenues in terms of goal difference. Clearly, there is a wide variation in these marginal revenues where most of the club-seasons are between log(10) and log(14) implying the the marginal revenues for a goal scored ranges between 22,000 and 1.2 million euro.

Table 6 summarizes the results of this exercise by league for all years and for

Figure 2: **Histogram marginal revenues firms for one goal; post 2008**



Based on the parameter estimates presented in Table 5

the years after 2008, when we can include financial data on all leagues. Over all clubs and countries an additional goal difference induces an average revenue increase of 311,000 euro (347,000 for the period since 2008), but the differences between the various leagues are huge. Over the years post 2008, an additional goal in the English top division leads to an additional revenue of 873,000 euro while in the French second division an additional goal generates no more than 68,000 euro.

7 The Degree of Assortative Matching

7.1 Descriptives

We now create productivity rankings of workers based on the estimated manager effects from equation (1) and rankings of firms based on the marginal revenues calculated from equation (2). To construct these rankings, we consider all workers and firms who appear in a worker-firm match at the start of the season, i.e., in the first game each club plays in each season.[10] For each year, we generate a separate

[10]In a robustness check we construct these rankings using each new match which originates in the dataset. We prefer the start of season rankings, because these matches occur after the off-season, which constitutes a period of several months for workers and firms to re-match in the

Table 6: **Marginal revenue estimates goal difference (1000 euro)**

	All		Post 2008	
1^{st} division				
Belgium	163	(117)	163	(117)
England	741	(511)	873	(566)
France	333	(298)	370	(326)
Germany	795	(619)	820	(632)
Italy	488	(418)	548	(449)
Netherlands	172	(171)	184	(182)
Portugal	194	(264)	193	(274)
Scotland	113	(157)	126	(180)
Spain	698	(847)	675	(852)
2^{nd} division				
England	102	(54)	120	(57)
France	60	(33)	68	(35)
Italy	69	(51)	72	(41)
Average	311	(434)	347	(476)

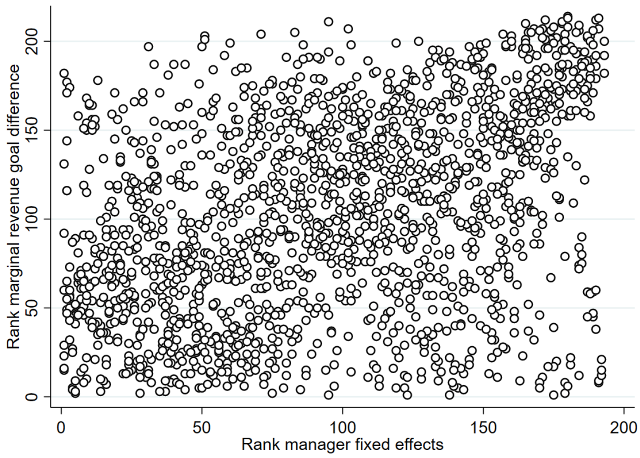
Note: Standard deviations in parentheses.

ranking for each of the national leagues in our database and a ranking for the overall European labor market. Taken together we get a panel of international and national rankings over our sample period such that we can compare the correlation at both levels year-by-year.

To gauge the relationship between the two productivity rankings, Figure 3 shows a scatterplot over all the yearly worker and firm rankings in our database. Although the spread is large there are fewer observations in the north-west and south-east part of the diagram so the overall patterns indicates a positive relationship between the relative ranking of a worker and firm in an employment match. Clearly, managers with high fixed effects are likely to be matched with firms that have a high marginal revenue of goal scoring. However, the relationship is far from perfect as there are also managers with high fixed effects that match with low marginal revenue firms.

labor market.

Figure 3: **Ranking worker effects vs. ranking firm marginal revenues**



7.2 Measuring Assortative Matching

To formally measure the degree of assortative matching we calculate the Spearman rank correlation between the rank of each firm and its worker within each country and in the combined dataset of all countries. In Table 7 we show the results from this calculation for the average correlation over the full sample length and the period after 2008, in which all countries are present in the data.

Panel a shows that the rank correlation over all countries has a value of 0.453 over the entire sample and 0.390 post-2008. Panel b shows rank correlations per country. The country-level correlations are uniformly positive and significant, except for Scotland post 2008. We therefore clearly find positive assortative matching between workers and firms in the managerial labor market. Moreover, there is little reason to conclude that the international labor market sees less assortative matching than each national market.[11] In itself this is not surprising as there are huge cross-country differences in productivity. As indicated before, wheres an

[11] In Appendix C we show rank correlations between fixed effects of workers and firms according to the traditional approach. Then we find evidence of significant negative assortative matching between workers and firms. We speculate that this is because measurement errors induce a spurious negative correlation between both types of fixed effects. Using two separate sources of information as we do removes the spurious negative correlation.

Table 7: **Spearman rank correlation between worker effects and firm marginal revenues**

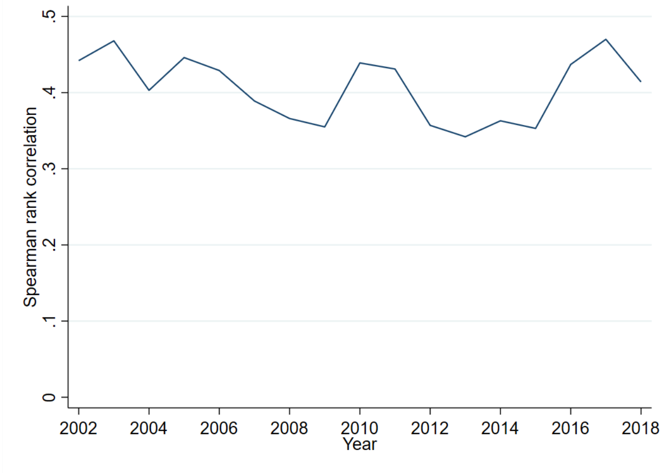
	All years		Post 2008	
a. Overall	0.452 ***	(2634)	0.390 ***	(1732)
b. Belgium	0.279 ***	(118)	0.283 **	(109)
England	0.477 ***	(727)	0.468 ***	(396)
France	0.406 ***	(558)	0.398 ***	(370)
Germany	0.261 ***	(106)	0.290 ***	(95)
Italy	0.420 ***	(575)	0.462 ***	(350)
Netherlands	0.584 ***	(211)	0.591 ***	(155)
Portugal	0.533 ***	(97)	0.528 ***	(94)
Scotland	0.236 ***	(115)	0.055	(42)
Spain	0.545 ***	(127)	0.496 ***	(121)
c. Country movers	0.623 ***	(758)	0.570 ***	(510)
Country non-movers	0.376 ***	(1876)	0.311 ***	(1222)
d. No Germany, Portugal, Scotland	0.486 ***	(2316)	0.449 ***	(1501)

Note: Number of observations in parentheses. We construct a separate ranking each time a new season starts using the observer worker-firm matches in the first game played. **: significant at 5%-level ***: significant at a 1%-level.

additional goal in the first division in England has a value of 876,000 euro a goal in the first division in the Netherlands has a value of 186,000 euro. Moving from the Netherlands to England allows the best Dutch managers to match with firms with substantially higher marginal revenues.

To supplement this analysis, we perform three robustness checks. First, we investigate whether the internationally mobile workers are responsible for the international assortative matching we uncover. We therefore repeat our analysis separately for managers who ever moved between countries and for managers who stayed in one country over their entire career. The rank correlations are shown in panel c of Table 7. Indeed for the managers who were active in different countries the magnitude of the correlation between their fixed effects and the marginal revenue indicators is substantially larger (0.623) than this correlation is for manager who were active in one country only (0.376). Clearly, the opportunity that many managers had to work in different countries increased the strength of assortative matching. Panel d of Table 7 shows the rank correlations if we remove all countries

Figure 4: **Spearman rank correlation over time**



for which we have fewer observations (Germany, Portugal and Scotland) from the sample. The rank correlation in the remaining observations increases somewhat but is not very different from the rank correlation in the overall sample. Finally, we also estimated the degree of assortative matching separately by season. As shown in Figure 4 assortative matching does not fluctuate much across seasons and is quite stable over time.

7.3 Evidence from Worker Mobility

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From the previous analysis it is clear that there is positive assortative matching in the sense that workers with a higher productivity in terms of goal differences are working at firms which obtain a higher marginal revenue from goal differences. The analysis is based on a static approach taking existing worker-firm matches as given. We can also exploit the labor market dynamics, i.e., movements of workers between firms. Our data contains information about 1256 workers moving between firms; 1045 moves are within countries and 211 moves are between countries. Of these moves about 60% is an upward move, i.e., a move to a firm with a higher marginal revenue of goal differences.[12] To investigate the determinants of the probability of an upward move we estimated a linear probability model in which in addition to yearly fixed effects we included the rank of the worker fixed effect and the rank of the marginal revenue of the firm in the year before the move. Table 8 presents the parameter estimates.

Table 8: **Parameter estimates probability of upward move**

	Between countries		Within countries		All moves	
Worker fixed effect	0.23	***	0.10	***	0.12	***
Firm marginal revenue	-0.33	***	-0.29	***	-0.28	***
Observations	211		1045		1256	
Percentage upward	52		54		54	

Note: Upward move is a change of job to a firm with higher marginal revenues; year fixed effects are included; parameter estimates of linear probability model multiplied by 100; ***: significant at a 1%-level.

Clearly, the ranking of the worker has a positive effect on the probability of an upward move. This is supportive evidence of positive assortative matching. The ranking of the firm marginal revenue has a negative effect on the probability of an upward move. This makes sense as it is difficult for a worker to make an upward move is he is already working at a firm with a high marginal revenue. The differences in parameter estimates between the different types of movement are small. Apparently, there is not much difference between workers moving within and across countries.

8 Conclusion and Discussion

Our study uses data from professional football managers to investigate whether there is positive assortative matching between high-skilled workers and firms both within European countries as well as across national borders. We derive a ranking

[12]Note that these numbers are smaller than the ones presented in Table 3 because of missing information about the marginal revenues of some firms.

of worker productivity by investigating how the performance of a club is affected by home advantage, the wage bill of both teams and unobserved time invariant effects of both clubs and managers. We gauge the productivity of firms by estimating revenue equations in which performance is one of the explanatory variables. From the parameters of the revenue equation we calculate the team-specific marginal revenues of additional sporting performance. We rank firms according to productivity using these marginal revenues.

We find a positive rank correlation between workers and firms, both nationally and internationally. From this we conclude that there is positive and substantial positive assortative matching in this labor market within countries and across national borders. This positive assortative matching is even more pronounced for managers that have at least moved once between countries. Our results therefore suggest that national borders do not prevent assortative matching between workers and firms within the European labor market for football managers. We interpret this as evidence that the labor market is highly integrated across national borders.

To some extent our main finding of positive assortative matching may be related to frictions being smaller in the labor market for football managers than they are in other labor markets. This is the case because it is easy to observe the performance of football managers, irrespective of location. To the extent that frictions in the labor market of football managers are related to information available, frictions will be lower. Nevertheless, also in other labor markets such as academia, R&D, high-end finance and top corporate management there is information about the productivity of workers that firms may use in their hiring strategies. Therefore, although our paper focuses on one particular industry and one particular group of workers, our results have broader implications than the industry we study. The incentives for our group of workers to move between firms are very comparable to the incentives high-skilled workers have in other industries. Positive assortative matching is likely to be a common phenomenon in many labor markets that have an international dimension.

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Appendix A: Information about our data

As shown in Table A1 our initial sample holds 71,270 games, which reduces to 49,124 games after imposing two restrictions:

1. Managers should be present in the dataset at least 35 times

2. Include only clubs for which financial information is available

The second restriction is mostly felt in Germany, Portugal and Scotland, where the accounting data has less coverage.

Table A1: Available games per league

	Time period	Initial sample	Net sample
First division			
Belgium	2008-2018	3,366	2,608
England	2000-2018	7,220	5,880
France	2003-2018	6,080	5,225
Germany	2007-2018	3,672	862
Italy	2002-2018	6,238	5,450
Netherlands	2005-2018	4,284	3,066
Portugal	2008-2018	2,750	1,049
Scotland	2000-2018	4,284	1,564
Spain	2000-2018	7,220	5,555
Second division			
England	2000-2018	10,488	7,582
France	2003-2018	6,080	4,548
Italy	2002-2018	7,780	4,334
Europe			
Champions League	2000-2018	1,038	813
Europa League	2000-2018	770	588
Total		71,270	49,124

Appendix B: Connection statistics

Moves between clubs and countries are crucial for the identification of the manager and club fixed effects. As argued by Andrews et al. (2008) and Jochmans and Weidner (2019), the variance and co-variance of fixed effects estimated on networks, which are only weakly connected, may be severely biased. This "limited mobility" bias goes down when there are relatively more links i.e., more workers move within the network of firms. In Table B1, we report a couple of statistics developed by Jochmans and Weidner (2019) to characterize the potential bias in our sample. First, we show λ_2, the second Eigenvalue of the connection matrix of our data-network. This is a measure of global connectivity of the network. An Eigenvalue approximating 0 indicates a sparsely connected network, which is detrimental to the precision of the parameter estimates. In our case, the Eigenvalue is substantially larger than 0, in comparison to the "problematic" empirical example Jochmans and Weidner (2019) provide. Then we look at the mean, median and standard deviation of $\mathbf{S}^{\dagger}$, the normalized Laplacian of the network. In order to allow good inference on the fixed effects, the mass of the distribution of this object should be close to 1. In our case, the mean in our net sample is around 1.4, with a fairly small standard deviation of 0.36. This number allows us to estimate the bias in the variance as a percentage of the observed large sample approximation of this variance. In our case these numbers come in at around 2.3 percent.

Table B1: Connection statistics manager-team network

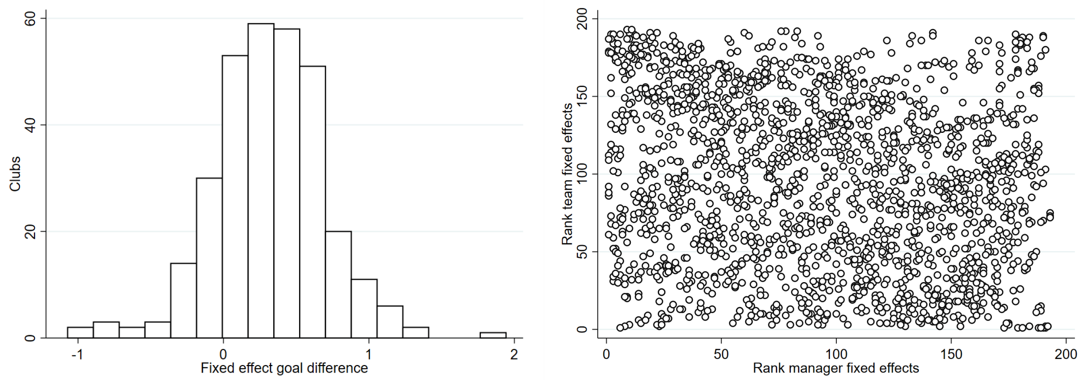
Eigenvalue (λ_2)	0.043
Mean ($\mathbf{S}^{\dagger}$)	1.41
Median ($\mathbf{S}^{\dagger}$)	1.35
Std. dev. ($\mathbf{S}^{\dagger}$)	0.36
Bias Var(FE)	2.26%

The connection statistics refer to the notation introduced in Jochmans and Weidner (2019).

Appendix C: Two-way fixed effects

The traditional approach to establish assortative matching is by investigating the correlation between managers fixed effects and club fixed effects as they are estimated based on equation (1). To illustrate that our findings in the main text are very different from those achieved by the traditional approach, in this sensitivity analysis we also use the firm effects of which the distribution is shown in the left-hand side of Figure C1. The range of the club fixed effects is similar to the range of the manager fixed effects. The right-hand side graph of Figure C1 shows the relationship between the rank of the manager fixed effects and the rank of the team fixed effects. The graph is not very informative about the nature of the relationship although it seems to be more a negative than a positive relationship. The negative relationship would be in line with our speculation that this is caused by measurement errors.

Figure C1: Histogram firm FEs and scatterplot two-way FEs



Based on parameter estimates for 678 managers and 316 clubs presented in Table 4

Table C1 shows the estimated rank correlations between the two fixed effects. Overall, there is a significant but small negative rank correlation. Thus, different our main findings the traditional approach would have wrongly concluded that there is negative assortative matching. The country-specific results vary a lot. There is a significant negative correlation between the two types of fixed effects in Belgium, England, France, Germany, Scotland and Spain. Furthermore, there is a significant positive correlation in the Netherlands and a positive but not significant correlation in Italy and Portugal.

Table C1: Spearman rank correlation two-way fixed effects

a.	Overall	-0.010 ***	(2980)
b.	Belgium	-0.387 ***	(170)
	England	-0.175 ***	(744)
	France	-0.327 ***	(584)
	Germany	-0.220 **	(111)
	Italy	0.049	(587)
	Netherlands	0.400 ***	(221)
	Portugal	0.059	(101)
	Scotland	-0.364 ***	(127)
	Spain	-0.229 ***	(335)

Number of observations in parentheses.

Clearly, the results from the traditional two-way fixed effects approach are very different from our results. As Bartolucci et al. (2018) argue, using information from two sources is more revealing about the strength and direction of assortative matching. Manager fixed effects derived from match level outcomes are indicative of the productivity of managers. Also using match level outcomes to capture the productivity of clubs does not seem to be appropriate. To establish the productivity of clubs an independent source of information, i.e., the revenues of the club, is more informative.