Job Matches and Mobility of High Wage Workers Across National Borders

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Abstract

We examine whether national borders hinder the assortative matching of high-productivity workers to high-productivity firms in a high-wage international labor market. We use a dataset of worker-firm matches from nine European countries over a span of 12 years. We rank employment matches along two dimensions: worker productivity, based on the estimated worker contribution to physical output, and firm productivity, measured as the capacity to transform physical output into revenue. The rank correlation between these two rankings is positive and significant within each country and across all countries. This "positive international assortative matching" suggests that national borders do not obstruct workers and firms from seeking high-productivity job matches in other European countries. The pattern of positive assortative matching arises as a result of the workers' initial job matches and their subsequent mobility.

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)). Evidence from the US confirms that workers dislike geographic distance to job opportunities, but this need not lead to significant mismatch in a national labor market when there are ample job opportunities close to the workers' residence (Marinescu and Rathelot (2018)). 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.

In this paper we analyse the strength and direction of assortative matching in a high wage international labor market: the European labor market for football managers.[1] By doing so, we assess whether national borders between European countries create market frictions hindering cross-border assortative matching of workers to firms.

Our dataset tracks worker-firm matches across nine European countries for 12 consecutive years. The number of worker-firm matches per year is around 225, which gives a total of 2,722 observations overall. They involve 868 unique workers (managers) employed by about 354 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) 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 rank 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.

There are several benefits of analyzing sports data to understand economic mechanisms including the functioning of labor markets (Palacios-Huerta (2023)). The data we use provide frequent and public observations on the performance of

[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.

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. 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 threefold. 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 introduce a novel way to establish worker productivity separate from firm productivity, which alleviates methodological concerns raised in the literature. Third, 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.

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

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. (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)).[2]

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 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

[2]Not all studies that derive both worker and firm fixed effects from one wage equation seem to suffer from bias. Dauth et al. (2022) for example study matching between workers and firms across Germany following the approach of Abowd et al. (1999). They aim to explain geographical disparities in labor market outcomes concluding that positive assortative matching is stronger in large cities.

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. Unlike most papers in the literature however, we do not observe the individual salaries of the workers in our sample.

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. 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 along the traditional two-way fixed effects 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.

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 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.[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. 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

[3] 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.

a firm's productivity ranking and that of its workers. 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 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 less high 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.

3 Data Sample and Sources

To construct our dataset we take 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 financial data coverage is sufficient as of this season and ends in 2018-19 to avoid interference of the COVID-19 lockdown. 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)). 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.

In the "Full Sample" column of Table 1 we show the number of worker-firm matches in our dataset split out by federation and season. For all federations, our sample includes the top division (indicated as D1 in the table). For larger federations with better financial data sources (England, France and Italy) we are also able to include the second tier (D1+D2 in Table 1). This difference largely explains the differences in the full sample tally across federations. The remaining difference is the result of varying numbers of clubs in the different divisions. Note that 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. As expected, the full sample size does not vary significantly over time. We have 2,722 worker-firm matches in our full sample. As explained in more detail in the next section, we need to observe the revenues of the club to estimate its productivity. For our estimates of worker productivity, we require

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

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. These restrictions reduce the number of worker-firm matches for which we can measure both worker and firm productivity to 2,229. We refer to this sample as the "Raw sample". Payroll information is not available for all clubs in the "raw" sample. If we include this as a control in our estimation of worker productivity, the number of observations reduces further to 2,148. We refer to this as the "Wage sample".

Table 1: **Worker-firm matches by federation and season**

	Full Sample	Raw Sample		Wage Sample	
Seasons	# matches	# matches	%	# matches	%
2007-08	228	158	69	152	67
2008-09	228	171	75	166	73
2009-10	225	181	80	174	77
2010-11	226	188	83	181	80
2011-12	226	186	82	179	79
2012-13	226	191	85	183	81
2013-14	226	205	91	196	87
2014-15	228	198	87	189	83
2015-16	228	191	84	186	82
2016-17	225	193	86	190	84
2017-18	228	193	85	184	82
2018-19	225	174	77	168	75
Federations	# matches	# matches	%	# matches	%
Belgium (D1)	195	131	67	131	67
England (D1+D2)	528	486	92	481	91
France (D1+D2)	480	441	92	441	92
Germany (D1)	216	132	61	120	56
Italy (D1+D2)	501	430	86	419	84
Netherlands (D1)	216	188	87	178	82
Portugal (D1)	202	126	62	116	57
Scotland (D1)	144	84	74	52	36
Spain (D1)	240	211	88	210	88
Total Matches	2,722	2,229	82	2,148	79
Unique Workers	868	601	69	551	63
Unique Firms	354	329	93	301	85

Note: Table displays the coverage of various samples used in producing the main empirical results on worker-firm matching; % = percentage of the full sample. D1 = Top division; D2 = Second tier.

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]

4 Estimating Worker and Firm Productivity

To gauge the degree of assortative matching we create two productivity rankings, one of workers and one of firms. We construct both rankings for each of the repeated cross-sections of employment matches we observe at the start of the season. We estimate these rankings using two separate regression models.

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. Following Peeters et al. (2022), we measure the productivity of 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 regress a club's output (the score difference in the games the club plays) on the inputs it uses (wage bill and home advantage) and a worker and club fixed effect. In the main body of the paper we report estimates including the wage bill (wage sample), our estimates excluding it (raw sample) can be found in the appendices. This estimation approach requires a sufficient number of mobile workers to connect clubs to allow the separate identification of worker and firm effects (see Abowd et al. (1999)). We further 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. We refer the interested reader to Appendix

[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.

A for more details on the estimation procedure and results.

We measure firm productivity 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 first regress club revenues on sporting performance, tangible assets, and fixed effects for the federation, division, season, and club. We then use the estimation results to calculate a club-year specific marginal revenue. Appendix B provides more details on the estimation procedure and results.

Taken together, the data requirements of our empirical approach imply that we can only estimate worker and firm productivity rankings for a subset of our full sample. In Table 1 we show how the composition of our full sample changes when we apply these criteria. In the raw sample we do not include the wage bill as a control in the estimation of worker effects. This allows us to estimate both firm and worker productivity for 2,229 of the 2,722 employment matches (82%) in the full dataset. When we add the wage bill, there is a further decrease to 2,148 observed matches, or 79% of the original sample. The drop is most pronounced in Germany, Portugal, Belgium, and Scotland, because the financial data for clubs in these federations is available less often. The sample is also reduced in the first and last years due to incoming and retiring workers with less games to their name than required for estimation.

In Table 2 we show the summary statistics by season and federation for the productivity estimates of workers and firms in the wage sample. 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 0.053. 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 -0.327 in Scotland to 0.360 in Spain. Firm productivity is measured in 1000s of euros revenue per 1 added goal difference. The overall average stands at 309k. 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.

5 Measuring Assortative Matching

Table 2: **Assortative matching between workers and firms**

		Worker productivity		Firm productivity		Spearman correlation	
	Obs.	Mean	(Std. dev.)	Mean	(Std. dev.)	Coef.	Sign.
Overall	2,148	0.049	(0.366)	326	(448)	0.461	0.000
Seasons							
2007-08	152	-0.005	(0.347)	258	(339)	0.330	0.000
2008-09	166	0.008	(0.382)	256	(317)	0.416	0.000
2009-10	174	-0.003	(0.378)	272	(359)	0.557	0.000
2010-11	181	-0.029	(0.349)	260	(344)	0.565	0.000
2011-12	179	-0.001	(0.354)	284	(394)	0.491	0.000
2012-13	183	0.001	(0.358)	281	(384)	0.393	0.000
2013-14	196	0.031	(0.354)	284	(391)	0.416	0.000
2014-15	189	0.047	(0.350)	321	(436)	0.395	0.000
2015-16	186	0.073	(0.337)	346	(460)	0.489	0.000
2016-17	190	0.110	(0.380)	394	(533)	0.499	0.000
2017-18	184	0.147	(0.370)	442	(584)	0.394	0.000
2018-19	168	0.193	(0.366)	507	(628)	0.517	0.000
Federations							
Belgium D1	131	-0.023	(0.404)	147	(102)	0.302	0.001
England D1+D2	481	0.032	(0.324)	456	(542)	0.576	0.000
France D1+D2	441	-0.026	(0.295)	192	(262)	0.535	0.000
Germany D1	120	0.065	(0.405)	751	(567)	0.229	0.012
Italy D1+D2	419	0.150	(0.273)	293	(343)	0.482	0.000
Netherlands D1	178	-0.215	(0.328)	156	(166)	0.480	0.000
Portugal D1	116	0.106	(0.455)	192	(256)	0.569	0.000
Scotland D1	52	-0.327	(0.552)	119	(143)	0.471	0.001
Spain D1	210	0.360	(0.311)	515	(688)	0.364	0.000

Note: All calculations are based on estimations in the wage sample. Worker productivity is expressed in added goal difference per game. Firm productivity refers to 1000 euros per marginal unit of goal difference.

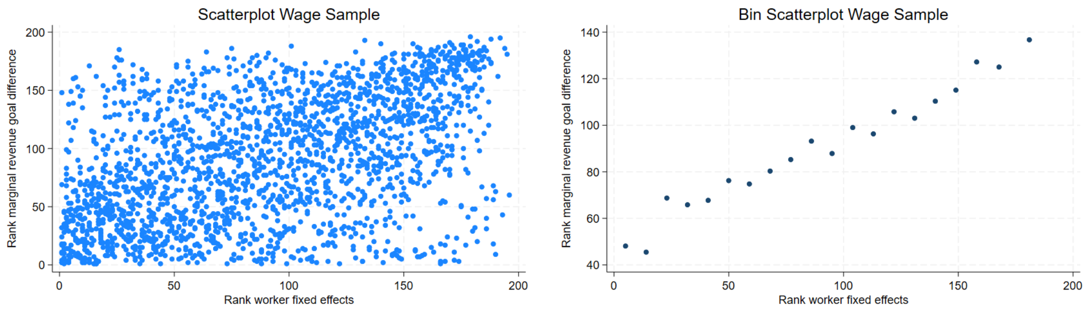
In Table 2 we measure the degree of assortative matching by calculating the Spearman rank correlation between each firm's productivity rank and the productivity rank of the worker it employs.[6] The rank correlation over all countries and seasons has a value of 0.461. In each of the individual year-by-year 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 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 2 shows the rank correlations within each federation over all seasons. These are also positive and significant, but on average not higher than the figure for the international labor market. 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 1 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. To make this pattern clearer we add a bin scatter plot of the same data in the right hand panel. The pattern emerging from 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.

To further investigate the international dimension of the assortative matching, Figure 2 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

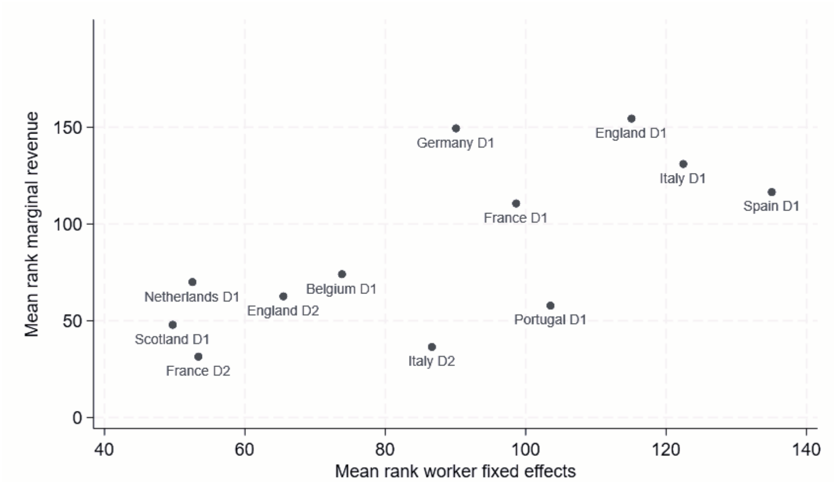
[6]This is for the wage sample. We show the equivalent table for the raw sample in appendix C, where we also conduct further robustness checks.

Figure 1: **Rank Correlation Worker and Firm Productivity**



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.

Figure 2: **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).

6 Worker Mobility and Initial Matching

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. We now examine the relative importance of these mechanisms in our dataset.

Table 3 gives an overview of the worker mobility in the wage estimation sample. The bottom row of the first three columns show that our sample consists of 2,148 observations of 297 firms (clubs) and 551 workers (managers). Of the 551 workers 79 are only observed once while for 472 workers we have multiple observations.[7] Of these 472 workers 285 did not change employer, 162 moved to a different employer within the same country and 26 moved to an employer of a different country (in our sample). So of all mobility movements in our sample about 13% is related to cross-country mobility. There are clear differences in worker mobility across countries. For example, managers in Italy are about twice as mobile as managers in England and about three times more mobile than those in France.

Table 3: **Worker Mobility**

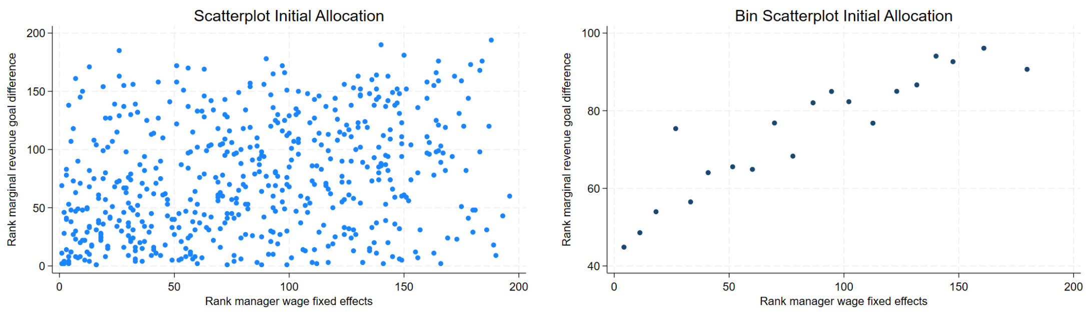
				Obs./worker		Worker mobility			
Federations	Obs.	Firms	Workers	1	> 1	No	W.C.	B.C.	Total
Belgium (D1)	131	19	40	8	32	17	12	3	15
England (D1+D2)	481	55	107	17	90	61	22	7	29
France (D1+D2)	441	51	101	16	85	66	18	1	19
Germany (D1)	120	17	32	3	29	21	6	2	8
Italy (D1+D2)	419	64	111	16	95	37	56	2	58
Netherlands (D1)	178	24	49	4	45	27	14	4	18
Portugal (D1)	116	24	38	3	35	17	15	3	18
Scotland (D1)	52	9	12	0	12	9	3	0	3
Spain (D1)	210	34	61	12	49	30	15	4	19
Total	2,148	297	551	79	472	285	161	26	187

Note: Mobility of workers in the wage sample; Obs. = Number of observations (worker-firm); Firms = Number of firms; Workers = Number of workers; W.C. = Within Country; B.C. = Between Country.

[7] Of the 297 employers 23 are observed only once. Note that the figures in Table 3 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.

We first examine the assortativeness of the initial employment match for the 551 workers in our dataset. Figure 3 shows scatter plots of the worker vs firm productivity rankings similar to Figure 1, but here 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 0.248. While this number is significant at the 0.1% level, it is lower than the overall correlation of 0.461. 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.

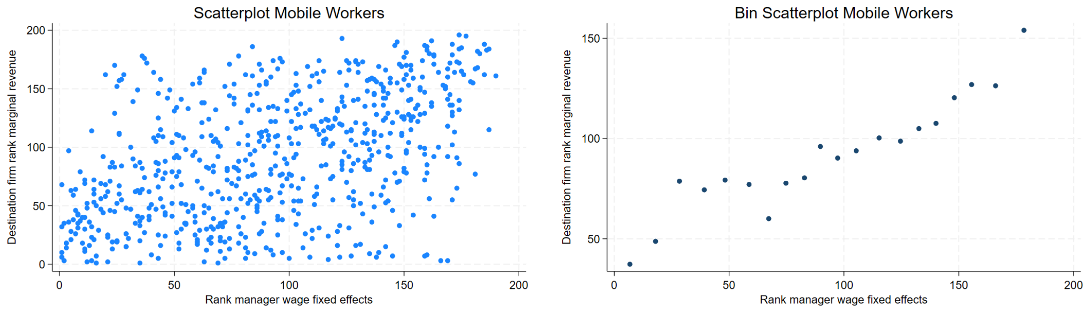
Figure 3: **Rank Correlation Worker and Firm Productivity; Initial Allocation**



Note: We plot the worker vs firm productivity ranking for the initial allocation. We define this as the employment match in the first season in which we observe each of the 551 workers in our sample.

Figure 4 shows the scatter and bin scatter plot between the productivity ranking of all mobile workers 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. The Spearman rank correlation for this sub-sample amounts to 0.480, which is significantly different from 0. In combination with Figure 3 this implies that the positive assortative matching we observe is related to both the initial situation and job mobility later on.

Figure 4: **Rank Correlation Worker and Firm Productivity; Mobile Workers**



Note: This graph is based on 665 observations of workers who changed firms. 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.

We complement the visual evidence from figures 3 and 4 with several regression analyses. First, we investigate the determinants of worker mobility. The results, reported in appendix D, support the idea that worker and firm productivity play a role in the probability that a worker moves employers from one year to the next. Second, we focus on the direction of these mobility events. In the first column of Table 4 we regress 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.[8] In the second and third columns we add personal characteristics (age and migrant status) and year and county 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

[8]We report the summary statistics for this estimation sample in appendix Table D.2

result is not significant throughout all models. 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 4: **Worker Mobility**

Dep. Var.:	Destination firm log productivity		
log(Firm productivity)	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 Conclusions

Labor mobility is an important and perhaps even essential determinant of the allocation of workers across firms. An optimal allocation between workers and firms occurs if high-productivity workers match with high-productivity firms. Worker mobility can be helpful if there is positive assortative matching related to changing jobs. Workers may find it attractive to change jobs if expected benefits of doing so exceed expected costs. In balancing these, not only monetary incentives are important. In addition to a wage increase when changing jobs physical, social and cultural differences between origin and destination may play a role. Because of the non-monetary costs, cross-border mobility is less likely to occur than within country mobility since crossing a border often coincides with changing social and cultural environment. From a welfare perspective cross-country mobility may be as important as within country mobility. In a tight domestic labor market it may be welfare improving if high-productivity firms can persuade high-productivity foreign workers to cross the border and accept job offers from these firms.

Our paper is on assortative matching between high-productivity workers and high-productivity firms in a European context. We distinguish between within-country and 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 sportive performance; the productivity of firms (clubs) is in specified in terms of revenues conditional on sportive 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 that 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. The positive correlation between productivity of workers and firms is present within countries as well as between countries. We show that average productivity varies a lot between countries. 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. Clearly, the labor market of professional football managers is a European labor market.

An important question is to what extent our findings have external validity. In other words, to what extent are our main findings typical for the labor market of international professional football managers or indicative for other labor markets. Clearly, due to popular sources and media reports, the labor market we study is characterized by easy observable productivity of both workers and firms. The labor market we study is homogeneous in the sense that workers have about the same tasks and firms have about the same production process. This labor market is characterized by high wages, very similar production processes, 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.

All in all, we conclude that there is positive assortative matching between workers and firms that does not seem to be hindered by country borders. At the high end of the labor market good matches between workers and firms are more important than country borders.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High wage workers and high wage firms. *Econometrica 67*(2), 251–333.

Andrews, M. J., L. Gill, T. Schank, and R. Upward (2008). High wage workers and low wage firms: Negative assortative matching or limited mobility bias? *Journal of the Royal Statistical Society. Series A (Statistics in Society) 171*(3), 673–697.

Bagger, J. and R. Lentz (2019). An empirical model of wage dispersion with sorting. *The Review of Economic Studies 86*(1), 153–190.

Bartolucci, C., F. Devicienti, and I. Monzón (2018). Identifying sorting in practice. *American Economic Journal: Applied Economics 10*(4), 408–38.

Bartz, K. and N. Fuchs-Schündeln (2012). The role of borders, languages, and currencies as obstacles to labor market integration. *European Economic Review 56*(6), 1148–1163.

Beerli, A., J. Ruffner, M. Siegenthaler, and G. Peri (2021). The abolition of immigration restrictions and the performance of firms and workers: Evidence from Switzerland. *American Economic Review 111*(3), 976–1012.

Bonhomme, S., K. Holzheu, T. Lamadon, E. Manresa, M. Mogstad, and B. Setzler (2023). How much should we trust estimates of firm effects and worker sorting? *Journal of Labor Economics 41*(2), 291–322.

Bonhomme, S., T. Lamadon, and E. Manresa (2019). A distributional framework for matched employer employee data. *Econometrica 87*(3), 699–739.

Dauth, W., S. Findeisen, E. Moretti, and J. Suedekum (2022). Matching in cities. *Journal of the European Economic Association 20*(4), 1478–1521.

Dorn, D. and J. Zweimüller (2021). Migration and labor market integration in Europe. *The Journal of Economic Perspectives 35*(2), 49–76.

Drut, B. and R. Duhautois (2017). Assortative matching using soccer data: Evidence of mobility bias. *Journal of Sports Economics 18*(5), 431–447.

Eeckhout, J. (2018). Sorting in the labor market. *Annual Review of Economics 10*(1), 1–29.

Eeckhout, J. and P. Kircher (2011). Identifying sorting—in theory. *The Review of Economic Studies 78*(3), 872–906.

Filippin, A. and J. C. van Ours (2015). Positive assortative matching: Evidence from sports data. *Industrial Relations 54*(3), 401–422.

Gandelman, N. (2008). Mobility among employers and assortative matching: Field evidence from soccer data. *Journal of Sports Economics 9*(4), 351–370.

Gautier, P. A. and C. N. Teulings (2006). How large are search frictions? *Journal of the European Economic Association 4*(6), 1193–1225.

Hagedorn, M., T. H. Law, and I. Manovskii (2017). Identifying equilibrium models of labor demand sorting. *Econometrica 85*(1), 29–65.

Head, K. and T. Mayer (2021). The united states of Europe: A gravity model evaluation of the four freedoms. *The Journal of Economic Perspectives 35*(2), 23–48.

Hoey, S., T. Peeters, and F. Principe (2021). The transfer system in European football: A pro-competitive no-poaching agreement? *International Journal of Industrial Organization 75*, 102695.

Jackson, C. K. (2013). Match quality, worker productivity, and worker mobility: Direct evidence from teachers. *The Review of Economics and Statistics 95*(4), 1096–1116.

Jochmans, K. and M. Weidner (2019). Fixed-effect regressions on network data. *Econometrica 87*(5), 1543–1560.

Johnson, J. E. and M. M. Kleiner (2020). Is occupational licensing a barrier to interstate migration? *American Economic Journal: Economic Policy 12*(3), 347–373.

Kelly, S. (2017). *The Role of the Professional Football Manager*. London and New York: Routledge.

Kleven, H. J. J., C. Landais, and E. Saez (2013). Taxation and international migration of superstars: Evidence from the European football market. *American Economic Review 103*(5), 1892–1924.

Kline, P., R. Saggio, and M. Sølvsten (2020). Leave-out estimation of variance components. *Econometrica 88*(5), 1859–1898.

Lopes de Melo, R. (2018). Firm wage differentials and labor market sorting: Reconciling theory and evidence. *Journal of Political Economy 126*(1), 313–346.

Marinescu, I. and R. Rathelot (2018). Mismatch unemployment and the geography of job search. *American Economic Journal: Macroeconomics 10*(3), 42–70.

Mendes, R., G. J. van den Berg, and M. Lindeboom (2010). An empirical assessment of assortative matching in the labor market. *Labour Economics 17*(6), 919 – 929.

Muehlheusser, G., S. Schneemann, D. Sliwka, and N. Wallmeier (2018). The contribution of managers to organizational success: Evidence from German soccer. *Journal of Sports Economics 19*(6), 786–819.

Palacios-Huerta, I. (2023). The beautiful dataset. *SSRN Electronic Journal*, 132.

Peeters, T., B. M. Mills, E. Pennings, and H. Sung (2021). Manager migration, learning-by-hiring, and cultural distance in international soccer. *Global Strategy Journal 11*(3), 494–519.

Peeters, T. and S. Szymanski (2014). Financial fair play in European football. *Economic Policy 29*(78), 343–390.

Peeters, T., S. Szymanski, and M. Terviö (2022). The survival of mediocre superstars in the labor market. *The Journal of Law, Economics, and Organization 38*, 840–888.

Peeters, T. and J. C. van Ours (2021). Seasonal home advantage in English professional football; 1974-2018. *De Economist 169*, 107–126.

Scarfe, R., C. Singleton, and P. Telemo (2020). Do high wage footballers play for high wage teams? The case of Major League Soccer. *International Journal of Sports Finance 15*, 177–190.

Van Ours, J. C. and M. A. van Tuijl (2016). In-season head-coach dismissals and the performance of professional football teams. *Economic Inquiry 54*(1), 591–604.

Appendix A: Estimating Worker Productivity

We estimate worker productivity, i.e., the productivity of football managers as follows. 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:

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

In equation (A.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.[9] The estimated parameter for playing talent β_{xl} is allowed to vary by the league in which the game takes place. We estimate the model both with (wage sample) and without (raw sample) this variable. 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. 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 (A.1) can be identified relative to a common benchmark when firms are connected to one another by mobile workers. Then, equation (A.1) can 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 (A.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 every game is used twice, once from the perspective of the home team and once from the perspective of the away team. Thus we identify the home advantage parameter as a simple indicator variable and the home and away manager effects are equal for each manager by construction.

We summarize the main estimation results of this analysis in Table A.1. For both the model with and without wage bills, the home advantage is highly significant in every country and division. In the raw sample, for example, the home advantage effect ranges from a low 0.26 goals in the first division in Scotland to a high 0.50 goals in the Dutch top league. The effect of the (log) wage sum is also

[9] 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.

Table A.1: **Parameter estimates worker productivity**

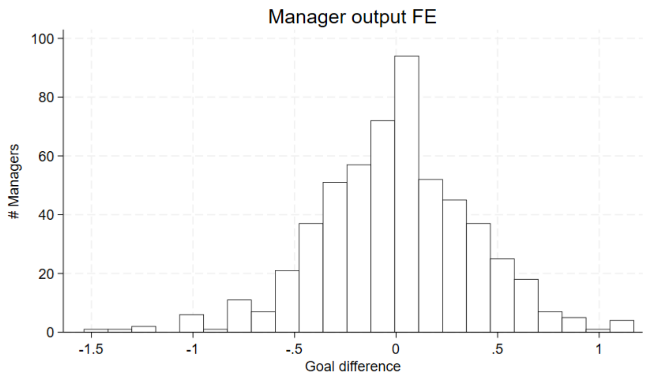
	Raw Sample		Wage Sample			
Dep.Var.: goal dif.	Home advantage		Home advantage		Log wage	
European cups	0.48***	(0.04)	0.49***	(0.04)	0.48***	(0.09)
Belgium D1	0.43***	(0.03)	0.43***	(0.03)	0.72***	(0.15)
England D1	0.39***	(0.02)	0.38***	(0.02)	0.42***	(0.11)
England D2	0.32***	(0.02)	0.32***	(0.02)	0.42***	(0.07)
France D1	0.39***	(0.02)	0.39***	(0.02)	0.53***	(0.09)
France D2	0.38***	(0.02)	0.38***	(0.02)	0.38***	(0.10)
Germany D1	0.37***	(0.03)	0.47***	(0.05)	0.62***	(0.16)
Italy D1	0.37***	(0.02)	0.36***	(0.02)	0.57***	(0.08)
Italy D2	0.35***	(0.02)	0.33***	(0.03)	0.26***	(0.08)
Netherlands D1	0.50***	(0.03)	0.49***	(0.04)	0.40**	(0.17)
Portugal D1	0.34***	(0.03)	0.37***	(0.04)	0.44***	(0.12)
Scotland D1	0.26***	(0.04)	0.36***	(0.07)	0.65**	(0.28)
Spain D1	0.47***	(0.03)	0.46***	(0.03)	0.33***	(0.09)
Explained variance						
Worker effects	$\frac{Cov(y,\mu)}{Var(y)}$	0.065		0.057		
Firm effects	$\frac{Cov(y,\gamma)}{Var(y)}$	0.122		0.040		
Other covariates	$\frac{Cov(y,X)}{Var(y)}$	<u>0.048</u>		<u>0.141</u>		
R-squared		0.236		0.238		
# Workers		637		555		
# Firms		329		301		
Observations		87,660		74,082		

Note: Every match is included twice in the analysis. Standard errors clustered at the match level in parentheses; *** significant at 1% level, ** significant at 5% level.

significant in every league and division although there are clear differences. In the wage model more than half 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 are able to attract better players and the influence of home advantage is well documented (Peeters and van Ours (2021)). Nevertheless, manager fixed effects and club fixed effects also contribute a lot to the explained variance in the goal difference. The contribution of club effects drops significantly in the wage bill model. Presumably the relative wage bill of a club is stable over time which leads to a high correlation with the club fixed effect. Remarkably, the overall variance explained is only marginally higher in the wage sample. Note that the number of estimated worker productivities is higher than the number of managers in the samples described in Table 1. This discrepancy has two causes. First, our dataset for estimating worker productivity includes all games in the season, while our sample of employment matches focuses on the first game of the season. It is possible that workers amass enough observations mid-season to allow us to estimate their worker effects, but are never in active employment in the first game of the season. In that case, they do not end up in the final sample, but are included here. Second, some clubs may report wage bills but not turnover. This means we can estimate the worker effect, but not the firm productivity. In that case, the worker also does not take part in the samples reported in Table 1.

The results presented in Table A.1 imply that worker productivity is important. Some managers are able to derive better results in similar circumstances. The manager 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. 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.[10]

Figure A.1: **Histogram worker fixed effects**



Note: Based on parameter estimates from model "Wage Sample" in Table B.1.

Figure A.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,

[10]By way of sensitivity analysis, we also calculated the correlation between the estimated manager and club fixed effects from equation (1) replicating the traditional approach to measure assortative matching. This (potentially downward biased) approach indicates negative assortative matching in our data.

and up to 2 goals compared to a really bad manager.

Appendix B: Estimating Firm Productivity

We estimate the revenue productivity for each firm (every football clubs). The revenue productivity is defined as the marginal revenue increase of an improvement in on-field performance. We model the revenues R_{lit} using a log-linear specification similar to the one used in Peeters and Szymanski (2014):

$$\log(R_{ilt}) = \beta_l y_{it} + \beta_x Z_{it} + \alpha_i + \tau_t + \lambda_l + \epsilon_{ilt} \tag{B.1}$$

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.

Table B.1: **Parameter estimates log revenues model**

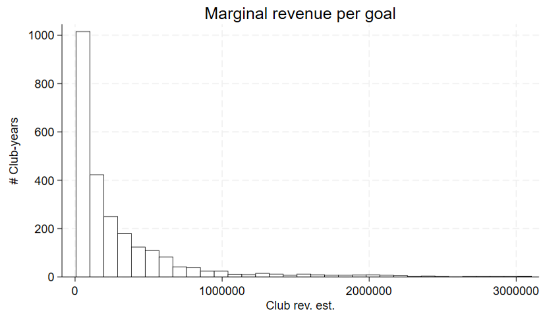
Goal difference	0.157***	(0.015)
Tang. assets	0.078***	(0.007)
Promoted	-0.112***	(0.019)
Relegated	0.473***	(0.032)
R-squared	0.959	

Note: 2,453 observations; club, season and division fixed effects are included; standard errors in parentheses. *** significant at 1% level.

The main parameter estimates of equation (B.1) are presented in Table B.1. 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. The number of observations in this estimation is higher than the raw and wage sample in Table 1. This is due to missing data to estimate the corresponding worker effect for these firms. The worker may have too few observations or not be part of the connected network. For the wage sample, the wage bill may also be missing for the club.

Using the estimates in Table B.1 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 B.1 shows the distribution of the marginal revenues in terms of goal difference. Clearly, there is a wide variation where most of the club-seasons have marginal revenues for a goal scored ranging between 20,000 and 1.2 million euro.

Figure B.1: **Histogram marginal revenues firms for one goal**



Based on the parameter estimates presented in Table B.1

Table B.2 summarizes the results of this exercise by league. Over all clubs and countries an additional goal difference induces an average revenue increase of 309,000 euro, but the differences between the various leagues are huge. An additional goal in the English top division leads to an additional revenue of 849,000 euro while in the French second division an additional goal generates no more than 56,000 euro.

Table B.2: **Marginal revenue goal difference**

League	Mean	Std. dev.	# Club-years
Belgium D1	143	102	134
England D1	849	570	218
England D2	104	52	255
France D1	327	318	219
France D2	56	30	215
Germany D1	729	557	132
Italy D1	485	370	219
Italy D2	60	34	210
Netherlands D1	151	164	196
Portugal D1	163	243	146
Scotland D1	86	123	98
Spain D1	488	672	216
Overall	309	438	2,258

Note: Amounts expressed in 1000 euros. Based on estimation results in Table B.1

Appendix C: Robustness assortative matching

In Table C.1 we repeat our analysis using the raw sample where we do not include the wage bill in the estimation of worker productivity. The results line up closely with the results for the wage sample presented in Table 2. Again, we find strong evidence of assortative matching within and across countries. All national rank correlations are positive and significant, presumably because the sample is larger in several federations. 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 C.1: **Assortative matching between workers and firms**

		Worker productivity		Firm productivity		Spearman correlation	
	Obs.	Mean	(Std. dev.)	Mean	(Std. dev.)	Coef.	Sign.
Overall	2,229	0.068	(0.381)	319	(443)	0.530	0.000
Seasons							
2007-08	158	0.015	(0.388)	252	(334)	0.385	0.000
2008-09	171	0.030	(0.395)	250	(314)	0.481	0.000
2009-10	181	0.027	(0.386)	267	(354)	0.622	0.000
2010-11	188	-0.010	(0.357)	255	(340)	0.589	0.000
2011-12	186	0.006	(0.378)	280	(390)	0.588	0.000
2012-13	191	0.020	(0.368)	278	(379)	0.509	0.000
2013-14	205	0.047	(0.372)	275	(386)	0.510	0.000
2014-15	198	0.067	(0.359)	310	(430)	0.477	0.000
2015-16	191	0.097	(0.361)	340	(456)	0.517	0.000
2016-17	193	0.135	(0.379)	391	(530)	0.538	0.000
2017-18	193	0.169	(0.382)	428	(576)	0.474	0.000
2018-19	174	0.211	(0.395)	497	(621)	0.618	0.000
Federations							
Belgium D1	131	0.015	(0.382)	147	(102)	0.324	0.000
England D1+D2	486	0.084	(0.346)	452	(540)	0.629	0.000
France D1+D2	441	-0.077	(0.342)	193	(262)	0.595	0.000
Germany D1	132	0.228	(0.432)	723	(549)	0.241	0.005
Italy D1+D2	430	0.113	(0.277)	287	(341)	0.497	0.000
Netherlands D1	188	-0.119	(0.347)	151	(163)	0.574	0.000
Portugal D1	126	0.254	(0.322)	188	(255)	0.579	0.000
Scotland D1	84	-0.321	(0.528)	97	(130)	0.397	0.000
Spain D1	211	0.389	(0.311)	511	(687)	0.409	0.000

Note: All calculations are based on estimations in the raw sample. Worker productivity is expressed in added goal difference per game. Firm productivity refers to 1000 euros per marginal unit of goal difference.

Table C.2 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 while it is markedly in the second tier.

Table C.2: **Assortative matching between workers and firms**

		Worker productivity		Firm productivity		Spearman correlation	
	Obs.	Mean	(Std. dev.)	Mean	(Std. dev.)	Coef.	Sign.
Sample							
Wage sample	2,148	0.048	(0.366)	326	(448)	0.461	0.000
No small fed.	1,729	0.060	(0.339)	325	(452)	0.534	0.000
First div.	1,497	0.109	(0.378)	436	(498)	0.425	0.000
Second div.	651	-0.091	(0.293)	73	(44)	0.125	0.001

Note: All calculations are based on estimations in the wage sample. Worker productivity is expressed in added goal difference per game. Firm productivity refers to 1000 euros per marginal unit of goal difference.

Appendix D: Additional Results Worker Mobility

Table D.1 shows details of the worker mobility between countries. Cross-country mobility is highest to and from England. As shown, from England, there are seven outward mobility moves, one to France, Germany, Italy, and the Netherlands and three to Scotland. There are also seven inward moves to England: one from Belgium, Germany, Italy, Portugal and Spain and two from the Netherlands.

Table D.1: **Worker Mobility by Federation**

From	To Bel	Eng	Fra	Ger	Ita	Net	Por	Sco	Spa	Total
Belgium	12	1	0	0	0	2	0	0	0	15
England	0	22	1	1	1	1	0	3	0	29
France	1	0	18	0	0	0	0	0	0	19
Germany	0	1	0	6	0	1	0	0	0	8
Italy	0	1	0	0	56	0	0	0	1	58
Netherlands	2	2	0	0	0	14	0	0	0	18
Portugal	0	1	1	0	0	0	15	0	1	18
Scotland	0	0	0	0	0	0	0	3	0	3
Spain	1	1	1	0	0	0	1	0	15	19
Total	16	29	21	7	57	18	16	6	17	187

We lack information about job offers, current wages, potential wage offers, willingness to move, duration of the current contract and whether or not a manager leaves a club voluntarily. Still, our dataset has information on worker characteristics, such as nationality, age and the estimated productivity of the employer and worker. We summarize this information in Table D.2.

Table D.2: **Summary Statistics Workers with Multiple Observations**

Variable	Obs.	Mean	Std. dev.	Min	Max
a. Workers with obs > 1					
Mobile	2,069	0.321	0.467	0	1
Mobile international	2,069	0.063	0.244	0	1
Firm productivity	2,069	327,422	450,259	7,587	3,104,674
Worker productivity	2,069	0.054	0.363	-1.534	1.173
Migrant	2,069	0.201	0.401	0	1
Age	2,069	49.5	6.99	19	73
b. Mobile workers					
Firm productivity	665	279,720	368,746	16,972	2,940,298
Worker productivity	665	0.048	0.331	-1.531	0.871
Migrant	665	0.195	0.397	0	1
Age	665	48.9	6.6	28	71

Note: Table contains summary statistics for sub-sample of workers with more than 1 observation in the dataset (top panel) and mobile workers (bottom panel). All variables are observed at the worker-year level.

We investigate potential determinants of worker mobility by regressing a mobility indicator on the variables from Table D.2. We take the log of the estimated firm marginal revenue. We further add the interaction between worker and firm productivity to the model. The idea is that if both are high the likelihood of moving is low as neither the worker nor the firm can improve their positions. Finally, we add country and year fixed effects to control for heterogeneity between federations and common time varying factors such as inflation. Table D.3 shows parameter estimates of linear probability regressions with various specifications including the rankings interaction term. We separate between overall mobility and international mobility.

Table D.3: **Determinants of Worker Mobility**

Dep. Var.	mobile yes/no				internationally mobile yes/no			
Log firm prod.	-0.026**	-0.017	-0.015	0.003	0.034***	0.034***	0.026***	0.036***
	(0.010)	(0.011)	(0.011)	(0.012)	(0.006)	(0.006)	(0.006)	(0.007)
Worker prod.	0.015	0.739***	0.708***	0.655**	-0.029*	0.030	0.088	0.173
	(0.031)	(0.259)	(0.261)	(0.259)	(0.016)	(0.145)	(0.148)	(0.160)
Log firm prod.*		-0.062***	-0.059***	-0.059***		-0.005	-0.010	-0.018
worker prod.		(0.022)	(0.022)	(0.022)		(0.013)	(0.013)	(0.014)
Migrant			0.013	0.057**			0.100***	0.107***
			(0.027)	(0.027)			(0.019)	(0.019)
Age			-0.394***	-0.220			0.002	0.059
			(0.143)	(0.139)			(0.073)	(0.073)
Observations	2,069	2,069	2,069	2,069	2,069	2,069	2,069	2,069
R-squared	0.003	0.007	0.011	0.094	0.021	0.021	0.045	0.077
Country FE	No	No	No	Yes	No	No	No	Yes
Year FE	No	No	No	Yes	No	No	No	Yes

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

The first columns of Table D.3 show the parameter estimates of overall mobility. The last 4 columns provide the parameter estimates for mobility between countries. The effects of firm productivity are mostly insignificant for the overall mobility probability, but we find a significant positive effect on international mobility. The worker effect has a positive impact on overall mobility, but not on international mobility. The interaction term is negative and significantly different from zero for overall mobility. Furthermore, migrant workers have a higher probability to move, especially internationally, i.e. if a manager is working in a country of which he does not have the nationality he is more likely to move. Finally, age has a negative effect on mobility, but this is not always significant.