

Best Score in the Match: Marginal Taxation and Labor Mobility in the European Football Market

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Abstract

We study the effect of top marginal tax rates on turnover and migration patterns of football players in 19 countries between 2006 and 2016. This phenomenon is analyzed both at the international and inter-regional level by exploiting national and regional variation of the effective marginal tax rate. We estimate two-sided matching model using a maximum score matching approach. This allows us to account for the competition on each side of the market, and get rid of factors affecting both the demand and supply side for which information is hardly available (namely, wages of top-level workers). The structural parameters of the underlying decision process are exploited to quantify the sensitivity of tax payers to taxation, the existence of sorting effects and the heterogeneity of these effects based on the ability of the player. Our results suggest that, once controlling for the matching structure and the observed dimension of the market, the estimates of taxpayers' sensitivity to taxation is lower than the ones presented in the previous literature. The elasticity of migration relative to the net-of-tax rate is 0.04 for natives and 0.80 for foreigners in the top 10% of the quality distribution while is around 0 if we consider all the population. However, the results suggest that lower taxes rates can increase the average quality of the country attracting more high-ability players who displace medium and low-quality players.

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Introduction

International mobility of high skilled workers (and the related erosion of national tax revenues) represents a crucial public policy issue, especially where occurring in an environment, such as the Europe, characterized by low mobility costs and relevant differences in top tax rates among countries.

In this context, governments are poorly able to collect fiscal revenue and redistribute income with progressive taxation, because ‘best’ taxpayers could leave the country, this way causing a reduction of the tax base, and ultimately of taxation revenue. On the contrary, countries could have incentives to attract high skilled workers given their high productivity and their ability to generate positive spillovers within a country. Therefore, understanding how the top earners location choices are sensitive to income taxes and which are the determinants of their patterns of migration is paramount.

The importance of high-skilled migration in general and its determinants has been highlighted in the literature¹ that has focused on the its effect on both receiving and sending countries (Stantcheva, Akcigit, and Baslandze, 2016).

Starting from the seminal contribution of Mirrlees (1982), this phenomenon has been deeply analysed by the theoretical literature in order to derive a model of optimal taxation in presence of international migration and tax competition across countries. For example, Lehmann, Simula, and Trannoy (2014) have derived a

¹See Kerr (2013) for an extensive review on this subject.

model of tax competition and international migration considering a framework with costly mobility, non-symmetric countries, individual heterogeneity in the distribution of workers' skills and simultaneous interactions between governments. This model has been further extended in Simula and Trannoy (2017) allowing governments to differentiate the tax schedule between native and foreign workers.

In spite of the presence of this body of theoretical literature, only recently this phenomenon has been empirically investigated, because of the lack of good micro data containing information about the citizenship and work history of workers. Migration choices of highly skilled workers² have been studied in a few empirical works. Kleven, Landais, Saez, and Schultz (2013) investigate the role of top tax rates on the international migration of football players in the European footballers market, whereas Stantcheva et al. (2016) study the effect of taxation on the location choice of inventors across United States and Europe. Preferential schemes for top earners in Denmark, and the difference in the elasticity of migration to taxation between foreigners and natives, are instead the focus of the study by Kleven, Landais, Saez, and Schultz (2014). Related to that, studies have been focusing more in general on inter-regional migration of high skilled workers (e.g. Moretti and Wilson (2017), who analyse the sensitivity of the migration choices of star scientist to changes on personal and business tax rates across US states, and Agrawal and Foremny (2018) who use administrative data to understand the role of taxation on the choices of migration of the entire universe of top incomes in Spain. All these works share the expected result that the probability of the worker to locate in one country or region is negatively affected by the marginal tax rate.

Starting from this literature, we aim to understand which are the economic

²An important share of these top earners are the so called superstars (Rosen, 1981)

determinants of the location process of top incomes using a new dataset on football players' careers and marginal taxation on both national and regional level. Our contribution is threefold. Our first and main research goal is the modeling of workers' location process by accounting for both the supply and the demand side (i.e. teams) of the market. In view of that, we consider the observed enrollment of football players as the outcome of market interactions between agents that compete in each side of the market to match with their preferred partners. In this framework, the income tax rate has an effect on the surplus arising from the employee-employer match and may impact on firms choices. Observed elasticity of taxable income and migration could actually be the byproduct of the interaction between the employee and employer responses (Stantcheva et al., 2016). An empirical approach consistent with this framework is, in our opinion, the maximum score matching estimator originally proposed by Fox (2018). Incidentally, this method allow us to get rid off of the lack of information on wages, which can be seen as an internal transfer inside the match. A second contribution is the use both regional and national variation in top tax rates. Finally, a dataset on the careers of football players richer than that by Kleven et al. (2013) is used, namely with information on several individual and team covariates (e.g. individual and team market value) that allow us to identify the distribution of the skills among the top 16 European leagues over the period 2006 - 2016.

Our results suggest two principal conclusions. Firstly, we find evidence of a positive sorting effect based on the quality of both teams and players, indicating that the matches between high quality teams and top players are more valuable. Secondly, we find a positive and significant effect of the net-of-tax rate on the utility of the match only when considering high-quality players. This result is

confirmed by our estimates of the elasticity of migration to taxation. Indeed, we find a positive elasticity of 0.135 only when we consider the players in the top 10% of the quality distribution. In particular, we find an elasticity of 0.04 for natives and 0.80 for foreigners. Moreover, the elasticities estimated considering players of lower quality are always negative or null. This suggests the presence of displacement effects where high-quality players migrate to countries with lower tax rates displacing medium and low quality players.

1 Background

The European football market is characterized by specific characteristics regarding teams, players and how their labor contracts are defined that derives from the particular nature of this sport.

In each European country there is one top-national league to which up to the 20 best football teams in the country take part. These teams can participate also to other competitions such as national or international cups³. The season of year t starts usually in August/September of year t and ends in May/June of year $t + 1$.⁴ This calendar poses some difficulties on the definition of the relevant tax rates. Following Kleven et al. (2013) we assume that the relevant tax rate for the year t season is the year t tax rate given that most of the teams' composition are decided before the beginning of the season.

Football teams are firms located in a specific city that use a specific stadium. This particularity hampers the possibility of relocating to other jurisdictions to

³In Europe there are two European competitions in which a restricted number of teams participates in, on the basis of their performances and country rankings.

⁴This rule is excepted by the northern countries (such as Norway and Sweden) where the year t season starts in March of year t and ends in November of the same year

take advantage of lower tax rates or other economic incentives. Hence, each observed migration pattern only depends on workers' mobility choices. Moreover, each team employ about 25-45 players in its main line-up. The number of players in teams depends on various factors such as the dimension of the market, number of fans, financial resources, number of competitions in which the team qualifies, and country-specific rules regarding the number of youths and national players. This number is naturally bounded by the fact that teams can employ only 11 players in each match. Given that the number of workers is neither fixed nor totally unbounded there could be some complication in the definition of the market structure. Indeed, if the number of players is relatively fixed we will have a rigid labor demand and, conversely, if this number is totally flexible we will have an elastic labor demand. This fact has important consequences on both the empirical model to estimate and the choice of the optimal tax schedule to apply. As explained in section 2, we overcome this problem by using an approach enabling us to let the market structure to be endogenously determined in equilibrium and, therefore, without ex-ante assumptions on the elasticity of the labor demand.

Teams and players sign contracts that define the affiliation duration, salary and other benefits related to players' performance, sponsorship and image rights on the merchandising sold by clubs. The combination of these payments makes very difficult to detect in a systematic way the overall wage paid by teams. If a player wants to change his team before the end of his contract or, conversely, if a team want to hire a new player employed by some other teams, the clubs involved can negotiate a transfer and a transfer fee. The latter is not part of the player's taxable income. This rules have been established after the so-called 'Bosman rule',

decided by the European Court of Justice in December 1995⁵. Each contract between team and player can be seen as the equilibrium outcome of a many-to-one two sided matching model with transferable utility (Fox, 2018). In this kind of models, the agents have a role defined ex-ante (worker or firm) and the matches are the outcomes of an interaction process between agents (Yang, Shi, and Goldfarb, 2009). The maximum score matching estimator (Fox, 2018) provides an empirical tool consistent with this theoretical framework by means of which to assess the effects of the marginal income taxation on the relocation and migration choices of European football players.

2 Theoretical Framework

Building on Kleven et al. (2013) and Lehmann et al. (2014), assume that in Europe there is a population P of potential football players with an endowment of ability $s_i \in S$, in a set of countries C . The utility of the player to play in country $c \in C$ is given by:

$$U(s_i, c) = \mu(c) + (1 - \tau_{ic}) \times w_i(s_i, c) \quad (2.1)$$

where $\mu(c)$ measures the preference of the player for country c , τ_{ic} is the marginal tax rate in country c , and w_i is the wage earned by the player i . Following Lehmann et al. (2014), we refer to Eq. (2.1) as the ‘gross utility’. This is the utility of player i if he decides to stay in country c and the level of net utility if he decides to migrate in country $c' \neq c$ supporting a cost of migration m . The cost of migration depends on a variety of underlying factors such as the home country, the financial

⁵See Kleven et al. (2013) for a description of the rules applying before the 1995 and for an analysis of the effects of this rule on the mobility of football players.

cost of migration, the differences in languages and culture, and the geographical distances⁶. Therefore, the player will choose to migrate from c to c' only if:

$$U(s_i, c) \geq (\max_{c'} U(s_i, c') + m) \quad \text{with } c \neq c' \quad (2.2)$$

namely, a migration will take place only whether the net utility that the player gains by migrating in country c' is bigger than the gross utility gained by staying in country c .

Kleven et al. (2013) show how this model yields the population of native and foreign players in each country on the base of the countries' characteristics and tax rates as done in. However, this model misses two important elements: the preferences of teams and regions' characteristics. Indeed, the location decisions of players are the outcome of a matching mechanism in which players and teams are competing in both sides of the market to match with their preferred partners. Moreover, each team is attached to a local stadium and a city and, therefore, the characteristics of the region that host the team play a fundamental role in this decision process.

To account for these two elements, we assume that in country c there is a set of regions $n \in N_c$ and a set of teams in each region n called A_n . In this case, the utility of the player i with ability s_i to play in team $a \in A_n$, in region n and in country c is given by:

$$U(s_i, n, c, a) = \mu(n, c, a) + (1 - \tau_{in}) \times w_{ai}(s_i, a, n, c) + I \times m \quad (2.3)$$

⁶These costs arise each time a player decides to migrate, even if he is not leaving his home country.

where $\mu(s_i, n, c, a)$ measures the preference of player i to play in team a , in region n and in country c , τ_{in} is the marginal tax rate in region n for player i , w_{ai} is the salary paid by team a to a player with ability s_i in region n and in country c , and I is the indicator function that takes value 1 if the player i is supporting the cost of migration m . Given that the teams are located in a specific region and in a specific country we can rewrite the Eq. (2.3) as:

$$U(s_i, a) = \mu(s_i, a) + (1 - \tau_{in}) \times w_{ai}(s_i, a) + I \times m \quad (2.4)$$

including all the informations regarding countries and regions in the subscript that refers to the team a . A key feature of Eq. (2.4) is that the income tax rate is region-specific. Indeed, as we will see in section 3.2, we are able to exploit the regional differences in tax rates in many countries of Europe and, therefore, we can model also the intra-national migration of footballers along with the international one.

Given Eq. (2.4), the player i is willing to play in team a only if the utility that he receives is greater than the utility that he can obtain when playing for other teams $a' \neq a$. Hence, he is willing to play for team a only if:

$$U(s_i, a) \geq \max_{a'} U(s_i, a') \quad \text{with } a \neq a' \quad (2.5)$$

Therefore, the player i is comparing every team in the market considering even where the team is located and the tax rate that he will face choosing that team. Consequently, we can indicate the mass of players that are willing to play in team

a as:

$$\bar{P}_a(\tau_{in}, w_{ai}) = \sum_{i \in P} 1[U(s_i, a) \geq \max_{a'} U(s_i, a')] \quad (2.6)$$

where $1[\cdot]$ is the indicator function that takes value 1 if the condition inside the brackets is satisfied. Therefore, $\bar{P}_a(\tau_{in}, w_{ai})$ indicates the mass of players for whom the condition (2.5) is satisfied.

At this point, we can model the decision process of teams that choose their partners from the set of players $\bar{P}_a(\tau_{in}, w_{ai})$. Let assume that teams A_n have a defined number of vacancy spots. If the team a hires the player i with ability s_i it can obtain the following net value:

$$V(s_i, n, a) = \pi(s_i, a) - w_{ai}(s_i, a, n) \quad (2.7)$$

where $\pi(s_i, a)$ is the value added by the player to the team, and $w_{ai}(s_i, a, n)$ is the salary paid by the team. With respect to the determinants of this net value two important elements have to be pointed out. First, the term $\pi(s_i, a)$ depends on the ability of the player s_i and on the specific characteristics of team a such as the number of the players that are already playing for it and their characteristics. Secondly, the wage $w_{ai}(s_i, a, n)$ depends on the ability of the player s_i , the team a , the region n , and, in general, the country c where the region n is located. Indeed, the salary paid by the firm could be lower than the marginal productivity of the worker because the team can have some market power given by the rigidity of the market for that particular type of player (Kleven et al., 2013). This market power can be heterogeneous among players and teams and can derive from various sources: dimension of the market in the region or in the country, prestige of the

team, scarcity of the player, prestige of the player, etc. It is important to note that, given our estimation strategy and the fact that we are observing team-players matches, we do not need to define explicitly the elasticity of the labor demand or the teams' market powers. In fact, we can let the structure of the market to be endogenously determined in the equilibrium. This strategy differs from the one used by Kleven et al. (2013) that assumes that the labor demand is either elastic or rigid.

In this setting the team a will choose to hire player i with ability s_i only if the value that it can gain from the hiring is greater than the one deriving from other players $i' \neq i$ and only if it has a vacancy spot. Therefore, it will hire the player i only if:

$$V(s_i, n, a) \geq \max_{i'} V(s_{i'}, n, a) \quad \text{with } i \neq i' \quad (2.8)$$

However, considering the condition (2.5) we know that only a subset $\bar{P}_a(\tau_{in}, w_{ai})$ of the population P is willing to play in team a . Hence, we can rewrite the (2.8) considering the condition (2.5) as:

$$V(s_i, n, a) \geq \max_{i' \in \bar{P}_a(\tau_{in}, w_{ai})} V(s_{i'}, n, a) \quad (2.9)$$

The inequality (2.9) shows that the team is actually choosing among the subset $\bar{P}_a(\tau_{in}, w_{ai})$ of players. In this way we are accounting for both players and team preferences. Therefore, if the conditions (2.9) and (2.5) are satisfied we will observe a match between player i with ability s_i and team a in region n . Consequently,

the number of players that are playing in team a in region n is defined as:

$$P_a(\tau_{in}) = \sum_{\bar{P}_a(\tau_{in}, w_{ai})} 1[V(s_i, n, a) \geq \max_{a'} V(s_{i'}, n, a)] \quad (2.10)$$

therefore, the mass of tax payers that are playing in the region n is defined as:

$$P_n(\tau_{in}) = \sum_{a \in A_n} P_a(\tau_{in}) \quad (2.11)$$

The Eq. (2.11) indicates the sum of the team-players matches that we are observing in one region n . This number depends on the characteristics of the region n in the country c (such as market dimension and marginal tax rate τ_{in}), the preferences of teams located in n and the ones of the players in the market. In this setting we are considering a situation where the players choose in which team they want to play. However, the results are identical even if we consider a situation where the teams move first and the players choose in the set of teams that are willing to hire them.

Finally, from Eq. (2.11) we can derive our parameter of interest: the elasticity of migration to taxation. This parameter indicates the sensitivity of tax payers' location choices to marginal tax rate and can be used to compute the optimal marginal tax rate in presence of migration. In particular, the elasticity measures the change in the number of taxpayers caused by a one percent change in the tax rate and is defined as:

$$\varepsilon_n = \frac{dP_n}{d(1 - \tau_{in})} \times \frac{1 - \tau_{in}}{P_n} \quad (2.12)$$

where $(1 - \tau_{in})$ is the net-of-tax rates that measure how much the disposable income of the players i increases when the wage w_{ai} increases by one Euro.

3 Data

3.1 Football Data

We have collected data on the careers of football players that have played in the first leagues of 19 European countries between the 2006 and 2016. The countries analyzed are: Austria, Belgium, Czech Republic, Denmark, England, France, Germany, Greece, Italy, Netherlands, Norway, Poland, Portugal, Russia, Scotland, Spain, Sweden, Switzerland, and Turkey. These countries have been chosen in order to consider all the top-25 European leagues according to the UEFA ranking.⁷⁸ These data are collected from various on-line sources such as *Transfermarkt.com*, *UEFA.com*, and *Footballsquads.co.uk*.

The most important source is *Transfermarkt.com*. This web site is one of the most important on-line community of football supporters in which are available data regarding various characteristics of teams and players. The information available at the player level consist in: the name, the age, the foot, the height, the position in the field, the club affiliation, the length of the contract, the nationality and the market value. The market value is particularly important because is used to assess the quality of the players. However, this variable has one important characteristic: it is not directly observed. Indeed, the market value is assessed by the registered users of *Transfermarkt.com* through a process of collective judgments (Peeters, 2018). This variable has been used previously in the sport economics literature by Bryson, Frick, and Simmons (2013) to investigate the salary return to the ability to play soccer with both feet, by Herm, Callsen-Bracker, and Kreis

⁷The UEFA ranking is a measure of the leagues' quality based on the past results of the teams

⁸We do not include countries such as Serbia and Romania because of the scarce availability of marginal tax data.

(2014) to evaluate the prediction powers of community evaluations related to real transfer fees, and by Peeters (2018) who compares the result in forecast of soccer results obtained using this market value or other standard predictor (e.g. the FIFA ranking). These works show that this variable is the best predictor of the players' quality. Moreover, the fact that the market value is not observed allow us to have a quality indicator even when the player has not changed the team.⁹ At the team level we observe: the country, the position in the league, the UEFA coefficient of the league and the city of the stadium where the team is situated. This latter variable is used to define the regions where the team is located and, therefore, the relevant marginal income tax rate.

Following Kleven et al. (2013), we restrict our sample to those players aged between 17 and 43 years and that are citizen of one of the countries in the sample. We exclude the other players because we cannot observe their work history and, therefore, we cannot compute counterfactual alternatives for their location choices. Intuitively, this choice is made because, otherwise, the non-European players would be always foreigners in every country and, therefore, we cannot identify the effect of their foreigner status on their location choices. Indeed, in that situation we cannot compare the country in which they play with the one in which they are born and, therefore, estimate the cost of migration from their home country. In order to follow this strategy we have dropped all the information that regards players for whom we do not observe the age.

Another characteristic of our dataset is that the matches that we observe could be the outcome of some trading strategy of teams. Namely, one team can buy a

⁹If the player has been playing in the same team for his entire career the *real* market value is unobservable since there is not a market transaction that regards the player.

player only as counterpart of some next transfer. Therefore, in these cases, we could observe the same player in different teams in the same season. To avoid these problems we have used the information on the starting date of the contracts keeping only the last contract signed by the player in each season. We exploit this information even in the cases when the player changes team in the middle of the season¹⁰ to impute the right tax rate. The last step of our strategy regards the nationality of players that have two or more citizenships. In these cases we keep the information on the first nationality that is selected in *Transfermarkt.com*. This citizenship is the mostly associated with the player football history¹¹.

Given this strategy, we have data on 13,868 players and 469 first-leagues teams observing 48,379 team-players matches.

3.2 Taxation Data

To choose the correct taxation data we need to solve two caveats: in which country (or region) the players are taxed and which kind of tax rate is relevant for their migration decisions. Indeed, the relevant tax rate for migration decision is the average tax rate (ATR). However, to use the ATR is problematic because it depends non-linearly on earnings, with the related endogeneity issues, and because we do not have data on the salaries earned by footballers. To solve these problems we exploit two characteristics of our sample. Firstly, given that footballers have to train daily, it is plausible that they have to live next to team's city. Hence, we can assume that they are taxed on the base of the tax system valid in the country (or the region) in which they work. Secondly, considering that footballers earn high

¹⁰In each league there is a market window that opens in the middle of the season. In Italy, for example, this window usually starts in January at the end of the first round of the league.

¹¹For instance, the national team of the player.

salaries compared to countries' top tax brackets for income taxes and payrolls, we can assume that the relevant tax rate is the marginal tax rate (MTR)¹².

To compute the marginal tax rate we have combined three types of taxes: the top marginal income tax rates, the employer and employee social security contributions, and the value added tax. Following Kleven et al. (2013) we define the marginal net-of-tax rate as¹³:

$$1 - \tau = \frac{(1 - \tau_i)(1 - \tau_w)}{(1 + \tau_{VAT})(1 + \tau_e)} \quad (3.1)$$

where τ_i is the top marginal income tax rate, τ_w is the uncapped social security contribution at the worker level, τ_{VAT} is the Value Added Tax, τ_e is the uncapped social security contribution at the employer level and τ is the combined marginal tax wedge. In this way, we can measure how much the disposable income of the worker increase when the marginal labor cost for the firm is increased by one Euro.

To compute this marginal net-of-tax rate we have collected tax data from various sources: OECD tax database, European Commission tax databases, the International Bureau of Fiscal Documentation country surveys, the PriceWater-sCoopers on-line sources, KPMG on-line sources, and various national sources. We cross-checked these sources with the tax rate time series available in Piketty, Saez, and Stantcheva (2014) in order to have a correct database.

In order to exploit both international and inter-regional variation we have collected data on both national and regional level. In particular, we observe regional variation of the marginal tax rates in 5 countries: Denmark, Italy, Norway, Switzer-

¹²Kleven et al. (2013) and Moretti and Wilson (2017) show that their results are similar using ATR instead of MTR.

¹³The derivation of the marginal net-of-tax rate is in the section A.1 of the appendix

land, and Spain. Moreover, we are able also to account for preferential taxation schemes for footballers or for top earners in many countries: Spain, Belgium, Netherlands, Denmark, France and Turkey. In these countries we observe that the marginal taxation is different for foreigner football players or for football players in general. This latter characteristic of our dataset permits us to analyze how the preferential schemes affect the distribution of skills within a country comparing the native and the foreigner elasticities of migration.

3.3 Descriptive Statistics and Graphical Evidence

Table 1 reports the descriptive statistics of our sample showing the information on the characteristics of players and marginal tax rates by country. From this table we can have a glimpse on the quality distribution of players. In particular, we can individuate a group of five countries (England, France, Germany, Italy and Spain) that have a share of players in the top 10% of the quality distribution way bigger than the average share in the sample. This pattern seems confirmed also looking at the share of players at the bottom of the quality distribution where these countries have the smallest shares of players of poor quality. Regarding the share of foreign players we can notice that England has a share of foreign players which is more than twice the average share in the sample (41.21%) followed by Germany (27.34%) and Belgium (24.30%)¹⁴. Columns 7 and 8 reports the top tax rates valid for native players and for foreigners. In particular, we observe a difference between tax rates for foreigners and natives in Belgium, Denmark, France, Netherlands and Spain. In these countries there are specific tax regimes for foreign top earners which aim to attract high skilled workers. For example, the so called *Beckham Law* in Spain

¹⁴In table A.1 in the Appendix we present the origin-destination flows by country-pairs

established a flat tax system with a tax rate 24% for workers with an income higher than 600,000 Euro from 2004 to 2010¹⁵. Column 9 reports, for each country, the difference between the highest and the lowest tax rates in the regions. We observe regional variation in 6 Countries: Denmark, Italy, Norway, Spain, Sweden and Switzerland. These differences are small in all the countries with the exception of Switzerland. However, the migration within country is likely less costly than the international one. Therefore, even a smaller difference in tax rates could cause a significant effect. For example, using administrative data on tax payers in Spain Agrawal and Foremny, 2018 finds that the probability of moving to one region increases by 1.5% when its tax rate decrease by one percent.

¹⁵See Kleven et al. (2014) for a comprehensive analysis of the Danish preferential system.

Table 1: Descriptive Statistics

| | N | Foreigners (%) | Age (years) | Top10 (%) | Top1050 (%) | Bottom (%) | τ_n | τ_f | Regional MTR Δ |
|---------------|-------|-------------------|----------------|--------------|----------------|---------------|----------|----------|-----------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| All Countries | 48379 | 17.73 | 25.14 | 9.40 | 37.62 | 52.98 | 57.01 | 50.47 | 0.93 |
| Austria | 2212 | 11.44 | 24.37 | 0.09 | 17.31 | 82.59 | 58.33 | 58.33 | 0.00 |
| Belgium | 2807 | 24.30 | 24.68 | 0.71 | 35.91 | 63.38 | 75.25 | 56.19 | 0.00 |
| Denmark | 2350 | 14.55 | 25.07 | 0.09 | 23.83 | 76.09 | 65.67 | 40.20 | 0.52 |
| England | 3409 | 41.21 | 25.62 | 36.73 | 45.23 | 18.04 | 59.40 | 59.40 | 0.00 |
| France | 3093 | 10.83 | 25.69 | 12.90 | 56.13 | 30.97 | 66.67 | 46.67 | 0.00 |
| Germany | 3819 | 27.34 | 24.29 | 16.05 | 46.79 | 37.16 | 55.54 | 55.54 | 0.00 |
| Greece | 3366 | 17.59 | 25.10 | 1.13 | 25.91 | 72.96 | 55.44 | 55.44 | 0.00 |
| Italy | 4634 | 15.28 | 25.79 | 17.95 | 43.94 | 38.11 | 56.19 | 56.19 | 1.07 |
| Netherlands | 3756 | 22.07 | 24.20 | 2.53 | 33.92 | 63.55 | 60.00 | 42.00 | 0.00 |
| Norway | 2005 | 16.51 | 25.46 | 0.00 | 22.64 | 77.36 | 60.90 | 60.90 | 1.71 |
| Portugal | 2354 | 10.96 | 25.53 | 5.69 | 35.43 | 58.88 | 70.54 | 70.54 | 0.00 |
| Russia | 2456 | 8.22 | 24.79 | 7.98 | 33.18 | 58.84 | 38.39 | 38.39 | 0.00 |
| Spain | 3795 | 16.81 | 26.24 | 20.13 | 57.87 | 22.00 | 55.29 | 35.92 | 2.82 |
| Sweden | 2494 | 8.38 | 25.26 | 0.12 | 14.84 | 85.04 | 73.65 | 73.65 | 1.63 |
| Switzerland | 1599 | 19.82 | 24.36 | 0.50 | 23.95 | 75.55 | 47.42 | 47.42 | 13.00 |
| Turkey | 4230 | 10.28 | 25.08 | 4.47 | 46.12 | 49.41 | 27.97 | 27.97 | 0.00 |

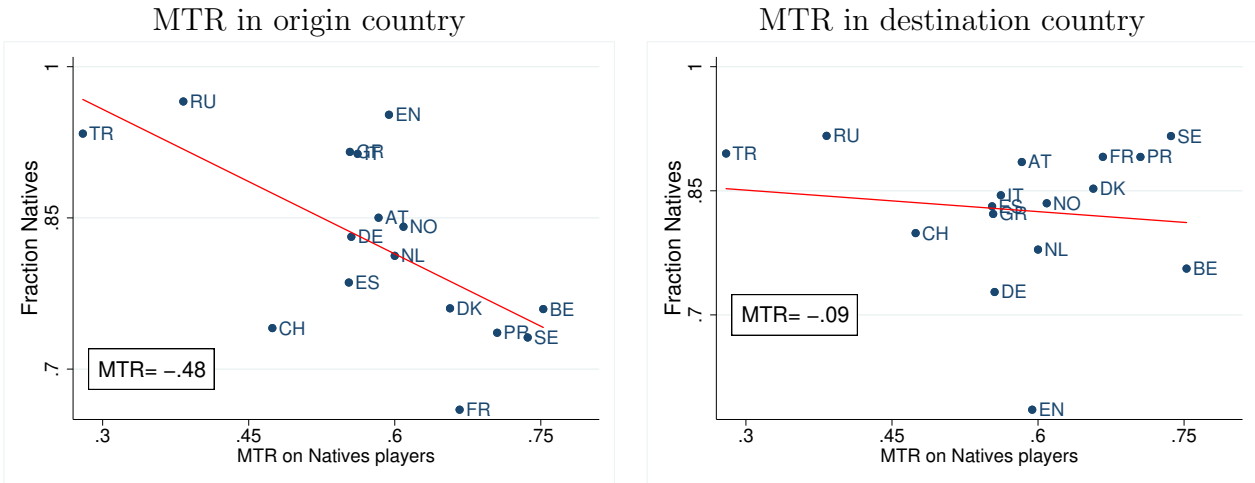
Notes: This table reports summary statistics for our sample covering the period 2006-2016. The sample includes the players that are citizen of one country in the sample and play in an European top league. Column (1) reports the number of player-team matches observed. Column (2) reports the percentage of foreign players. Column (3) reports the average players' age in years. Columns (4), (5) and (6) report the shares of players that are, respectively, in the top 10% , between the top 10% and the top 50%, and below the top 50% of the quality distribution computed according to the players' market values. Column (7) and (8) report the top marginal tax rate applying, respectively, to native and foreign players. Column (9) reports the variation in the regional tax rates.

Figure 1 shows some graphical evidences of the relationship between MTR and the out-migration of native players (Panel A) and between MTR and the in-migration of foreign players (Panel B). Each plot presents the coefficient associated with MTR coming from a linear regression between players' shares, MTR and a constant. This coefficient can be roughly interpreted as an indicator of the correlation between the two variables. In each panel we define the MTR in two different ways: on the left we use the MTR valid in the origin country and, on the right, the one valid in the destination country. Focusing on the Panel A, we can notice that the share of native players in a country is strongly correlated with the the origin country's MTR and weakly correlated with the destination country's one. This intuition is confirmed in Panel B where we have a strong positive correlation only between the fraction of players that leave their country of origin and the MTR in the origin country.

The difference between these two types of correlation seems indicate that the players are more interested in the MTR valid in their own country than in the one of the destination country. This could indicate that the player is always comparing his own home country's MTR against the MTR of the destination country. We account for this in our estimation strategy in two ways. Firstly, we control for a dummy that indicate whether the player is native of one country or not. Secondly, our estimation strategy is based on a comparison between a observed match and all the feasible counterfactual matches. Therefore, if the player is still in his home country, the estimator compare the MTR of the origin country with all the MTR valid for every counterfactual match.

The plots of figure 1 shows the average correlation between the effective tax rates and the migration patterns assuming that the effect is homogeneous among

Panel A: Out-migration of native players



Panel B: In-migration of foreigner players

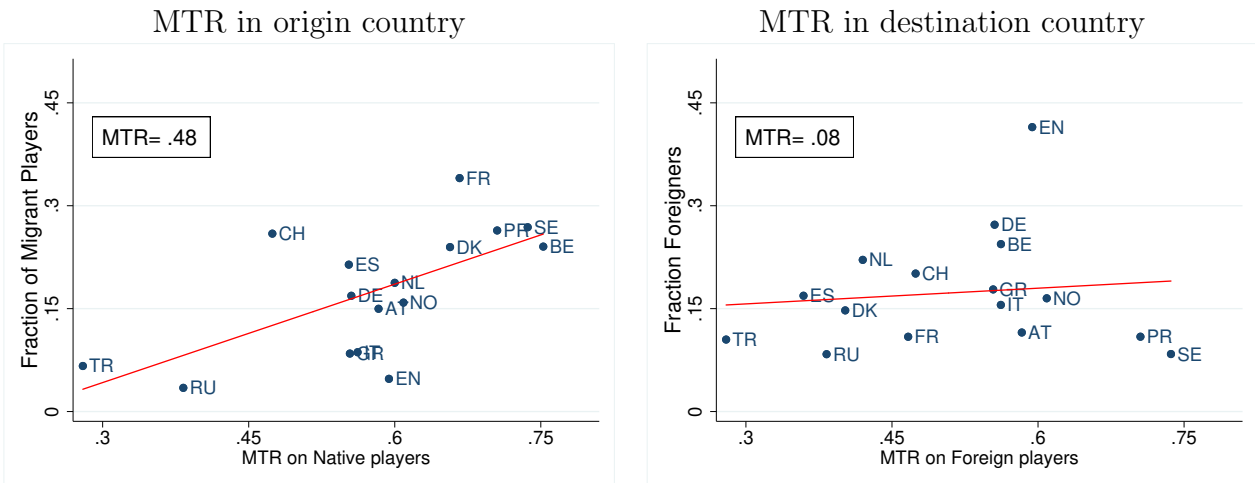


Figure 1: Cross-Country Correlation between Tax Rates and Migration, 2006-2016

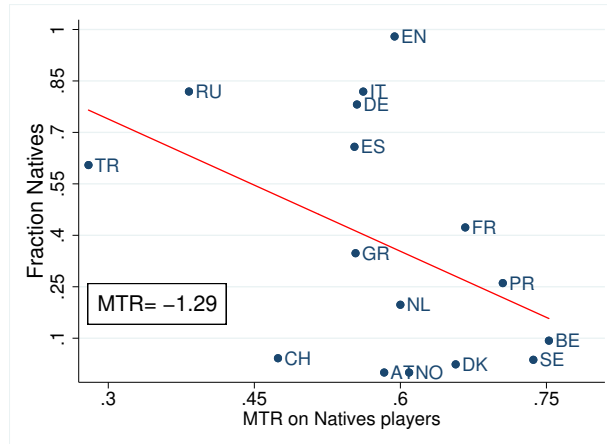
Notes: Each dot stands for one country: AT=Austria, BE=Belgium, DK=Denmark, EN=England, FR=France, DE=Germany, GR=Greece, IT=Italy, NL=Netherlands, NO=Norway, PR=Portugal, RU=Russia, ES=Spain, SE=Sweden, CH=Switzerland, TR=Turkey. The two panels shows the relationship between the fraction of natives and foreign players in each country with the MTR valid in the country of origin (on the left) and in the country of destination (on the right). Panel A focuses on the fraction of natives while Panel B regards the fraction of foreign players. In each plot we show the coefficient of the relevant MTR coming from a linear regression of the shares against MTR and a constant. All the plots refers to the entire period 2006-2016.

all the sample. However, as shown in Kleven et al. (2013) and Stantcheva et al. (2016) the effect of the MTR could differ on the base of the worker's ability. Therefore, in figure 2, we present the correlation between the share of natives and the MTR in the origin country splitting our sample in three subgroups: players in the top 10% of the quality distribution, players in between the top 10% and the top 50%, and players at the bottom of the quality distribution (below the 50%). We present the symmetric results for foreign players in the figure A.1 of the appendix.

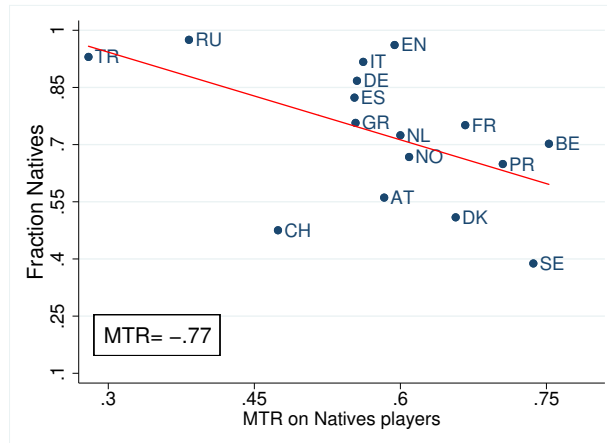
From figure 2 we can see that the relationship between the share of natives and the MTR in the origin country depends on the position of the player in the quality distribution. Indeed, the effect of MTR seems stronger for players with an higher quality. This suggest that a higher tax rate could cause a reduction in the quality of players in the country. This effect could be due to two different cause: the relevance of the MTR and the market power of the player. Relating to the first, an higher market value could be related to an higher wage for the player. Therefore, in this cases, the MTR could be more relevant given that the more is higher the income the more the ATR is similar to the MTR. Hence, the indicator of the position of the player in the quality distribution could be seen as an index of the intensity of the treatment given by the tax rate (Stantcheva et al., 2016). Relating to the second cause, a player with higher quality might have better job offers in the international market making easier for a high-quality player to leave the country and avoid the MTR of his origin country. Moreover, the players with lower quality might be entrapped in their home country and fill the spots leaved by the high-quality players. Hence, in a context of rigid demand there could be a mechanism where the high-quality players that leave the countries are replaced by the low-quality ones and, on the other hand, the low-quality player in a country with lower

Out-migration of native players by quality

Top 10% of the quality distribution



Top 10% to Top 50% of the quality



Below the 50% of the quality distribution

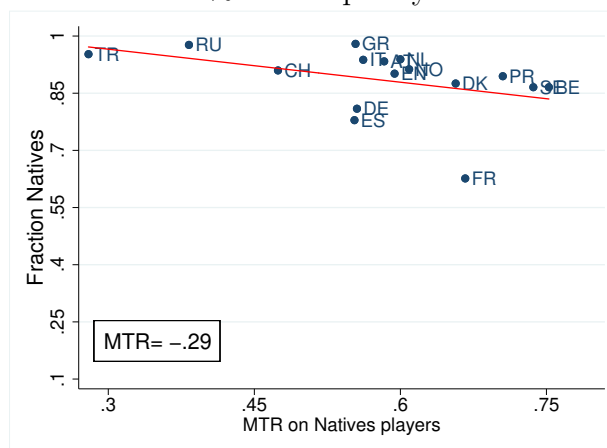


Figure 2: Cross-Country Correlation between Tax Rates and Shares of Natives by Quality, 2006-2016

Notes: Each dot stands for one country: AT=Austria, BE=Belgium, DK=Denmark, EN=England, FR=France, DE=Germany, GR=Greece, IT=Italy, NL=Netherlands, NO=Norway, PR=Portugal, RU=Russia, ES=Spain, SE=Sweden, CH=Switzerland, TR=Turkey. The three plots show the relationships between the fraction of native players in each quality subgroup and the MTR valid in the origin country. In each plot we show the coefficient of the relevant MTR coming from a linear regression of the shares against MTR and a constant. All the plots refers to the entire period 2006-2016.

tax rates are displaced by the high-quality foreign players. We account for this feature in two ways: exploiting the heterogeneity of the effect of marginal taxation through dummy variables indicating the position in the quality distribution, and estimating the elasticity of migration considering that the vacancy spots in each country are fixed.

4 Maximum Score Matching Approach

In this paper we take advantage of the maximum score matching approach (MSM) developed in Fox (2018). The MSM is a semi-parametric estimator based on the single agent multinomial choice maximum score developed by Manski (1975) that allows the researcher to estimate the parameters underlying the matching process between two types of agents in a specific market. This estimator detains various advantages compared to the standard discrete choice approaches used in the previous literature. Firstly, it allows the estimation of parameters underlying the matching process without having data on wages. This characteristic is particularly important in our case given that the data regarding the players' wages are not available, and that the contracts between players and teams are characterized by various bonuses and benefits that are not observable. Secondly, it allows a more general definition of the error term than the classical type I extreme value used in Logit models. Thirdly, its computational simplicity enable us to use a not artificially limited set of alternatives and individual covariates. Moreover, it ensures the validity of the estimates in spite of considering a subset of all potentially available choice alternatives (Fox, 2007).

The MSM has been used in the literature in several different fields. For exam-

ple, Yang et al. (2009) estimate the brand alliances between basketball players and teams; Mindruta, Moeen, and Agarwal (2016) compare the MSM with standard discrete choice estimators in a context of strategic alliances in the biopharmaceutical industry; Baccara, İmrohorođlu, Wilson, and Yariv (2012) quantify the effects of network externalities on choices of faculty regarding offices in a new building. Moreover, the MSM is analyzed in the survey on the applications of empirical matching models made by Chiappori and Salanié (2016).

The MSM is based, in our case, on the concept of many-to-one two-sided matching model(Fox, 2018). In this model the agents have a role defined ex-ante (one can be either player or team) and the matches are the outcomes of a process of interaction between agents that take their decisions interdependently. This model is based on the concept of local production function that is defined as the sum of the utilities of agents that participate in the match. In particular, if we observe, in a market m , the set of matches ω_m between team a and players P_a , and team b and players P_b , we can write the local production function of this set of matches as:

$$\pi(\omega_m) = \sum_{i \in P_a} [V(s_i, n, a) + U(s_i, a)] + \sum_{i \in P_b} [V(s_i, n, b) + U(s_i, b)] \quad (4.1)$$

where the terms in the brackets are the agents' utilities defined using equations (2.4) and (2.7). This set is a pairwise stable equilibrium if no coalition of agents prefers to deviate from the observed matches. This concept of equilibrium is similar to the best response condition. Indeed, given the rest of matches, the two agents forming the coalition compare the utility under the current relationship with the one of that they would gain in the counterfactual matches (Kim, 2018). Therefore,

if we define as $\tilde{\omega}_m$ the counterfactual set of matches where at least one player from P_b is matching with team a and one player from the set P_a is matching with team b , the set ω_m is a pairwise equilibrium if:

$$\pi(\omega_m) \geq \pi(\tilde{\omega}_m) \tag{4.2}$$

This equilibrium concept has some important consequences. First, if the condition (4.2) is satisfied we have that a *rank order property* holds (Fox, 2007):

$$Pr(\omega_m|a, b, P_a, P_b, m) \geq Pr(\tilde{\omega}_m|a, b, P_a, P_b, m) \tag{4.3}$$

The rank order property states that the probability to observe the actual set of matches is greater than the one of observing the counterfactual set of matches. This useful property can be used to define the objective function of the MSM in a way that is similar to the usual maximum likelihood estimator (Fox, 2007). The second advantage of this equilibrium concept is that we can use the inequalities defined in (4.2) to estimate the model without having data on the equilibrium wages. One drawback of this strategy is that we cannot use variable that are agent-specific but we need to use match-specific variables given by the interactions between the characteristics of teams and players. Section A.2 of the appendix shows the algebraic derivation of the MSM inequalities that allow us to estimate the model without having data on wages but prevent us to use agent-specific regressors¹⁶.

In order to define the objective function of the MSM we need to define the

¹⁶Namely, the wage is one agent-specific regressor that is canceled out from the inequalities comparing the two different set of matches.

parametric local production function of the set of matches ω_m as:

$$\pi(\omega_m) = \sum_{\omega_i \in \omega_m} (\pi(\omega_i)) = \sum_{\omega_i \in \omega_m} X(\omega_i)' \theta + \varepsilon_{\omega_i} \quad (4.4)$$

where ω_i is one match of the set ω_m , $X(\omega_i)$ is the matrix of match specific variables, θ is the vector of parameters that measure the effect of the variables on $\pi(\omega_m)$, and ε_{ω_i} is the unobservable component of the local production function of the match ω_i .

The MSM assumes that agents have preferences over the observables characteristics of the partners. This assumption lead to two main consequences. Firstly, the estimate of the local production function is semi-parametric. This means that we can estimate parametrically the observable component of the local production function of the set of matches ω_m and non-parametrically its unobservable component. Secondly, we do not need to define a specific distribution for the unobservables.

In order to have a consistent estimator of the parametric local production function we need that the following assumptions are satisfied:

- The unobservable component and the observable component of the local production function are uncorrelated;
- The unobservable component is *i.i.d.* across matches
- The conditional distribution of the unobservables conditioned on the observable component $F(\varepsilon_{\omega_i} | X(\omega_i))$ is continuous and exchangeable.¹⁷

¹⁷ $F(\varepsilon_{\omega_i} | X(\omega_i))$ is exchangeable if $F(\varepsilon_{\omega_i} | X(\omega_i)) = F(\rho(\varepsilon_{\omega_i}) | X(\omega_i))$ where ρ is a permutation. This concept is closely related to the *i.i.d.* assumption.

- The parameter space θ is compact

Given these assumptions and the semi-parametric nature of this estimator we can rewrite the (4.2) using only the observable components of the parametrical local production function as:

$$\sum_{\omega_i \in \omega_m} X(\omega_i)' \theta \geq \sum_{\tilde{\omega}_i \in \tilde{\omega}_m} X(\tilde{\omega}_i)' \theta \quad (4.5)$$

Finally, we can use the condition (4.5) to define the objective function of the MSM as:

$$\max_{\theta} Q_M(\theta) = \sum_{m=1}^M \sum_{g=1}^{G^m} 1 \left[\sum_{\omega_i \in \omega_m} X(\omega_i)' \theta - \sum_{\tilde{\omega}_i \in \tilde{\omega}_m} X(\tilde{\omega}_i)' \theta \geq 0 \right] \quad (4.6)$$

where M is the number of observed markets, G^m is the set of inequalities in each market¹⁸, and Q_M is the score function that we need to maximize. The logic behind this maximization is very simple: every time that the condition (4.5) is satisfied we add 1 to the score function. Therefore, when we reach the maximum of Q_M we will have identified the parametric local production function with the set of parameters θ that maximize the objective function. The most important characteristic of this objective function is its computational simplicity. Indeed, to evaluate this objective function we do not need to non-parametrically estimate the choice probabilities, the distribution of unobservables or to compute integrals used with the maximum likelihood approaches (Fox, 2018).

The objective function (4.6) is a step function. This aspect complicates both the maximization and the computation of the standard errors. These problems are solved using a differential evolution algorithm that allows the maximization of a

¹⁸In each inequality we consider a different counterfactual set of matches where we exchange a different coalition of players among teams.

step function and a sub sampling procedure to compute the interval of confidence (Politis, Romano, and Wolf, 1999; ‘Inference for identifiable parameters in partially identified econometric models’).

We implement the MSM in R using a modified version of the toolkit provided in Santiago and Fox (2008). The new code is able to handle a huge amount of data more efficiently in order to allow us to estimate this model in a setting characterized by a huge number of agents in each side of the market. In the next section we show the procedure used to estimate this model in our context.

4.1 Estimation Strategy

In order to estimate the effect of the marginal taxation on the location choices of footballers, we use an estimation strategy that is defined to account for the specific characteristics of the European football market and of the MSM estimator.

First, we need to define the set of independent markets for the estimation. The markets are independent in the sense that one agent cannot compete in more than one market. Hence, given that the players play in different positions we separate the players in offenders, defenders, midfielders, and goalkeepers (Yang et al., 2009). With this separation we account for the fact that players are more likely to compete with players in the same position of the field. Indeed, it is implausible that a goalkeeper or a defender is competing with an offender to match with its preferred team. However, the players can change their role in their careers and, therefore, compete in more than one market. To avoid this we define each season as a separate market obtaining 44 markets (11 years for 4 positions). Hence, in each market we will have on the supply side the players of one specific position

in a specific season and on the demand side the teams. Given this definition the teams are seen as the collection of different position-specific unities.

Secondly, we define the match specific variables that characterized our local production function in order to understand the determinants of footballers' location choices. The effect of tax rate on local production function is explored defining our variable of interest as the interaction between *level of player's quality* and *net-of-tax rate*. In this way, we are able to understand if there is heterogeneity in the effect of marginal taxation based on the ability of players and if there are sorting effects based on the net-of-tax rate. As we have seen in section 1 we use, as year- t season tax rate the tax rate that was valid at the beginning of the season. The quality of player quality is defined on the base of his market value. Specifically, we divide the players in three subgroups on the base of their position in the quality distribution in each year: players in the top 10%, players between 10% and 50% and players below the 50% of the quality distribution. In order to do this we define one quality-indicator variable for each subgroup.

The second determinant of the migration of top incomes that we want to exploit are the sorting effects based on quality of players and teams. Therefore, we define the second variable as the interactions *player quality* with *team quality* defined as the sum of the market values of the players. This variable allow us to understand if there is some positive sorting effect between teams and players based on the quality of both agents and how these characteristics influence the local production function of the match. Therefore, we expect that the higher the quality of players and teams the higher is the probability to observe a match between these agents. Both team and player quality are normalized to be comprised between 0 and 100. Moreover, we explore also the existence of some sorting effect based on the age of

the player interacting *young* with *team quality*. The dummy variable *young* takes value 1 if the player's age is lower than 25 years. With this indicator we want to understand if there is some sorting effect based on the age of the players other than on their quality. As we will see in the results, these two variables have also a role of control for the effect of the marginal taxation. Indeed, we will exploit the heterogeneity of the effect related to the team quality interacting it with quality indicators of players in order to understand if there is any heterogeneity in this sorting patterns, and to separate the effect related to the level of player's quality from the effect of the net-of-tax rate.

The third determinant that we want to assess is given by the cost of migration. With respect to this variable we include in the specification the *native status of the player*.¹⁹ With this variable we can estimate the effect of the cost of migration in a foreign country on the local production functions of the matches. This variable is used also as reference point for the interpretation of the results.

Third, we define the inequalities used in the objective function of the MSM. These inequalities are defined based on the conditions derived in the theoretical framework in section 2 and in section A.2.

Finally, we estimate the local production function by maximizing the objective function defined by Eq. (4.6). To maximize this objective function and identify the vector of parameters we need to fix one coefficient to +1 or -1 (Fox, 2007). This restriction is due to scale identification. Indeed, given the semi-parametric nature of the estimator we can identify the set of coefficient up to an order-preserving transformations of the parameters (Manski, 1975)²⁰. This means that, as in stan-

¹⁹The native status is a dummy variable that takes value 1 if the player is playing in his home country.

²⁰Namely, the same matching patterns can be generated by an infinite variety of set of coeffi-

dard discrete choice approaches, we can interpret only the relative magnitude of the coefficients. We choose the +1 or -1 on the bases of the goodness of fit given by the ratio between the value of the score function and the number of inequalities used (Fox, 2007). We fix the coefficient related to the *native status of the player* to +1 or -1 on the base of the percentage of satisfied inequalities.

Given our estimate of the local production function we are able to understand the determinants of migration patterns highlighted previously and to assess their relative importance in the location process of the football players.

4.2 The Elasticity of Migration

The standard strategy used to estimate the elasticity of migration is to use the probabilities estimated through a discrete choice model to compute the marginal effects and the changes in each country's populations deriving from a change in the net-of-tax rate. However, the semi-parametric nature of the MSM does not allow a direct estimate of the probability to observe the matches and, therefore, to compute the marginal effects. In this cases Manski (1975) suggest 2 different approaches. The first approach is to assume an ex-post distribution for the errors to estimate the probability to observe a match. However, this will result in a loss of the advantage to use a more general definition of the error terms. Moreover, this approach does not ensure that the number of predicted matches will be equal to the one observed. This can arise complication in the computation of the elasticities because we cannot properly account for the rigidity of the demand and for eventual displacement effects between different categories of players. The second

cients, which differs only by a constant that multiplies all the coefficients.

is to estimate the probability of the match non-parametrically.²¹ However, this procedure could be computationally expensive in our case given the dimension of our sample.

A third possible strategy is to estimate the elasticities through a simulation approach. With this approach we can use our MSM estimates of the local production function to simulate the matching assignments. Then, we can simulate the variation in the number of tax payers caused by a change in the net-of-tax rate of one standard deviation and compute the elasticity of migration using Eq. 2.12. The matching assignments are simulated using the algorithm used in Schwert (2018). This procedure consists in:

1. Compute the local production function for each potential player-team match in each market according to our estimates;
2. Sort all the possible matches by the estimated local production function values;
3. Select the most valuable matches in a descending order.

This procedure is carried considering that each player can match only with one team in each market and that the teams have a maximum number of vacancy spots. Indeed, we account for the size of each market in each country fixing the number of possible match to the sum of the observed quotas of each team in the market. We repeat this procedure until we reach the observed number of matches and the teams' quotas are filled. With this strategy we have three main advantages: we do not need to assume any error distribution, the procedure is computationally

²¹In a previous version of Fox, 2018 the author suggest to use the sieve methods.

less costly than a non-parametric technique and, we can account for the observed market structure. Moreover, this strategy permits a better understanding of the results of the structural model estimated with the MSM.

With this procedure we are able to estimate the sensitivity of the footballers to the marginal tax rate on both regional and national level. Moreover, we will be able to understand how this elasticity changes when the quality of the players changes.

4.3 Results

Table 2 presents the results of 5 different specifications of the match local production function. The table shows the estimated vector of coefficient, their 95% interval of confidence, the number of inequalities used and the percentage of inequalities satisfied. As seen in section 4 we compute the 95% interval of confidence through a sub sampling procedure. Namely, we estimate the same specification across 200 random samples of 5 markets each time. Given that the rate of convergence is $\sqrt[3]{N}$, the empirical sampling distribution of our vector of parameters is (Schwert, 2018):

$$\tilde{\theta}_s = \left(\frac{n_s}{N}\right)^{1/3} (\hat{\theta}_s - \hat{\theta}) + \hat{\theta} \quad (4.7)$$

where $\hat{\theta}_s$ is the estimate from the subsample s , $\hat{\theta}$ is the estimate from the full sample used in the estimation, n_s is the dimension of the sample s and N is the number of observation in the estimation sample. We construct our 95% confidence interval taking the 2.5th and the 97.5th percentile of the empirical distribution of θ_s . Therefore, our interval of confidence can be asymmetric. One coefficient is not statistically significant if the interval contain the value 0.

Table 2: Maximum Score Matching Estimation

| | MSM | MSM | MSM | MSM | MSM |
|---|-----------------|-----------------|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) | (5) |
| Native | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | Superconsistent | Superconsistent | Superconsistent | Superconsistent | Superconsistent |
| $(1 - \tau) \times Top_{10}$ | 0.405 | 0.700 | 0.118 | 0.147 | 0.129 |
| | [0.092 0.606] | [0.513 1.195] | [0.012 0.211] | [0.055 0.303] | [0.012 0.257] |
| $(1 - \tau) \times Top_{1050}$ | 0.408 | 0.727 | -0.000 | -0.001 | -0.001 |
| | [0.183 0.605] | [0.644 1.072] | [-0.051 0.037] | [-0.032 0.026] | [-0.027 0.045] |
| $Quality_{team} \times Quality_{player}$ | 47.882 | 22.219 | | | |
| | [25.732 | [-11.137 | | | |
| | 117.626] | 74.952] | | | |
| $Quality_{team} \times Top_{10}$ | | | 0.563 | 0.644 | 0.620 |
| | | | [0.493 0.589] | [0.601 0.689] | [0.545 0.674] |
| $Quality_{team} \times Top_{1050}$ | | | 0.004 | 0.094 | 0.067 |
| | | | [-0.075 -0.006] | [0.057 0.113] | [0.014 0.094] |
| $Quality_{team} \times Young$ | | 0.000 | | 0.070 | |
| | | [-0.002 0.000] | | [0.065 0.103] | |
| $Quality_{team} \times Top_{10} \times Young$ | | | | | 0.001 |
| | | | | | [-0.001 0.005] |
| $Quality_{team} \times Top_{1050} \times Young$ | | | | | 0.003 |
| | | | | | [0.000 0.004] |
| % of Inequalities satisfied | 93.18% | 93.63% | 93.28% | 94.52% | 93.88% |
| % of Inequalities used | 30% | 30% | 30% | 30% | 30% |
| N. of Inequalities used | 9046359 | 9046359 | 9046359 | 9046359 | 9046359 |

Notes: The parameter on Native is fixed at +1. The estimates of this parameter with a smaller number of inequalities find an estimate of +1, instead of -1. Given that the parameter can take only tow value (+1,-1) its estimate is super-consistent. See Fox (2018) for details on super-consistency. All the variables are expressed in logarithms. Each estimation uses a sample equal to the 30% of the entire set of inequalities. The 95% confidence interval are estimated through a sub-sampling procedure across 200 random samples of 5 markets at a time.

Moreover, in each estimation we use a random sample of 30% of the entire set of inequalities. Indeed, Fox (2010) suggest that in the estimation is possible to use a subsample of all the feasible inequalities in order to reduce the computational burden²². We have run the estimation several times to ensure the stability of the results.

From table 2 we can see that the variable *Native* is estimated with a coefficient of +1. This result is obtained estimating two times the same specification with the coefficient of *Native* fixed to +1 or -1 and choosing the specification that satisfies the higher number of inequalities. Indeed, this number can be seen as an measure of the model's goodness of fit. Unsurprisingly, the positive coefficient indicate that the matches between a team in a country and a player citizen of that country are more valuable. All the other variables presented in table 2 are expressed in logarithm. Column 1 presents the estimates relative to a model where the local production function depends only on the net-of-tax rates for players interacted with the players' quality indicators and the interaction between team and players quality. In the other models we extend this specification considering that the sorting effect based on quality can be heterogeneous adding interactions between $Quality_{team}$ and players' quality indicators and with the variable *Young*. Looking at the coefficients, we can see that the ones attached to the net-of-tax rates changes strongly across the models. In particular, we have that this coefficients remain stable after the introductions of the interactions between $Quality_{team}$ and players' quality indicators. This indicates that the in the first two specifications the net-of-tax variables are capturing also a pure quality effect that is not captured by the interaction between team and player qualities. However, the coefficients remain

²²The entire set of inequalities correspond to a matrix with 30,154,530 rows.

Table 3: Maximum Score Matching Estimation

| | Rescaled Clogit | MSM |
|------------------------------------|-----------------|--------------------------|
| | (1) | (2) |
| Native | 1.000 | 1.000 |
| | | Superconsistent |
| $(1 - \tau) \times Top_{10}$ | 0.363 | 0.147 [0.055 0.303] |
| $(1 - \tau) \times Top_{1050}$ | 0.165 | -0.001 [-0.032 0.026] |
| $Quality_{team} \times Top_{10}$ | 0.335 | 0.644 [0.601 0.689] |
| $Quality_{team} \times Top_{1050}$ | 0.065 | 0.094 [0.057 0.113] |
| $Quality_{team} \times Young$ | -0.016 | 0.070 [0.065 0.103] |
| % of Inequalities satisfied | | 94.52% |
| % of Inequalities used | | 30% |
| N. of Inequalities used | | 9046359 |

Notes: MSM is estimated using a random sample of 30% of the set of feasible inequalities. $(1 - \tau)$ is the net-of-tax rate, Top_{10} is 1 if the player is in the top 10% of the quality distribution, Top_{1050} is 1 if the player's quality is between 10% and 50% of the quality distribution. All the variables are expressed in logarithms. Column 1 reports the coefficient of a CLogit estimate that are rescaled so that the coefficient on Native is equal to 1. Column 2 presents the result of MSM estimates. The 95% confidence interval are estimated through a sub-sampling procedure across 200 random samples of 5 markets at a time.

stable even after the introduction of the player quality indicator in column 5. This could indicate that the net-of-tax variables are capturing a pure tax effect separated from the effect of the sorting on qualities captured by the interactions between $Quality_{team}$ and players' quality indicators. Given this interpretation and the fact that the model in column 4 is the one that satisfies the highest number of inequalities we base our interpretation and the estimation of the elasticities on the model in column 4. To simplify the interpretation, in table 3 we present

the results of our preferred specification along with a rescaled Conditional Logit (CLogit). This CLogit is estimated with the same specification of the MSM model but rescaling the coefficients so that the one attached to *Native* is equal to one²³. The interpretation of the coefficients is not straightforward. Indeed, as in every discrete choice approach, one can interpret the coefficients only with relationship to a baseline given by a match between a foreign low-quality player older than 25 years and a low quality team. Moreover, we can interpret also the sign and relative magnitude of coefficients. With respect to this point, we can see that the coefficient estimated with the CLogit relative to the net-of-tax rate are always bigger in magnitude than the ones of the MSM. This suggest that the estimates of the sensitivity of location choices to taxation could be biased for two reasons. Firstly, the CLogit does not account for the matching structure of the market. Secondly, to not account for wages and transfers between teams and players could be an important source of biases given the importance of these variables in the location decision process of tax payers. With respect to the MSM results we can highlight some interesting elements. Firstly, the most important element of the local production function is given by the variable *Native*. This could be due to the fact that most of the matches observed are between native players and teams. However, from this result we can infer that even in our context the cost of migration plays a fundamental role in the location decision process of individuals. The second result is given by the interpretation of the effect of taxation. Once we control for the effect of team and players quality, the contribution in the local production function of the net-of-tax rate is limited and significant only for players in the top

²³For comparisons with the standard discrete choice approach, in table A.2 of the Appendix we present the estimates of a CLogit with the same specifications presented in table 2 without rescaling the coefficients

10% of the quality distribution. This suggest that the more valuable matches are the one between an high-quality player and a team in a region with lower tax rates. Moreover, the results suggest that, *ceteris paribus*, the net-of-tax does not play an important role when the matches include a player of medium or low quality. This seems in line with the graphical evidence presented in figure 2. However, in a context of rigid demand, a change in the net-of-tax rate could affect medium and lower quality players through displacement effects. Indeed, the increase in the number of high-quality players in one country could displace medium and low quality players. Whit respect to the sorting effect based on qualities, the model suggests that the most valuable matches are the one between top-players and high quality teams. Indeed, the positive coefficient indicate that the two qualities are complement in the local production function. The last regressors suggest that the matches between a young player and an high quality team is more valuable than a match with an old player.

To better understand these results and to have a direct measure of the sensitivity of tax payers we present also the results given by our estimate of the elasticity of migration to taxation. In table 4 we compare the goodness of prediction of our simulation strategy with two standard approaches used to compute the matching probabilities. In the first we use the probabilities estimated with a CLogit. In the second we assume *ex-post* a distribution for the error term given by the type I extreme-value distribution²⁴ to compute the matches probabilities. As we can see from table 4 our approach is able to predict correctly the 28.38% of observed matches while the CLogit does not predict a positive number of matches and the

²⁴This is the standard error distribution assumed by the multinomial and the conditional Logit models

Table 4: Results of the Estimation of Probabilities and Matches

| | Observed Matches | Predicted Matches | % Of Predicted Matches | % Of Correctly Predicted Matches |
|------------|---------------------|----------------------|------------------------------|---|
| | (1) | (2) | (3) | (4) |
| CLogit | 5215 | 0 | 0% | 0% |
| Type I EV | 5215 | 54 | 1.04% | 11.11% |
| Simulation | 5215 | 5215 | 100% | 28.38% |

Notes: This table compares the prediction power of three approaches: CLogit, post-estimation assuming a Type I Extreme Value distribution for the errors and our simulation strategy. Column (1) reports the number of observed matches. Column (2) reports the number of predicted matches for each model. In the first two lines a match is predicted when the probability estimated is greater than 0.5. Column (3) reports the percentage of predicted matches. Column (4) reports the percentage of correctly predicted matches.

post-estimation strategy predict correctly only the 11.11% of observed matches.

Given these results we simulate the matching assignments in order to have an estimation of the elasticity of migration to taxation.

Table 5 presents the result of our simulation approach. In particular, we estimate the elasticities of different groups of according to whether they are foreigners or natives and their quality indicator.

It is important to note that our simulation approach keep fixed the number of taxpayers in each country. Therefore, the elasticity of migration considering all the population is 0 by definition. However, even the general elasticity of natives and foreigners is around 0. This could be related to the fact that, as seen in table 3, the effect of the net of tax rate is significant only for top players. Indeed, if we look to the elasticities of top players we can see that the effect of an increase of one standard deviation of the net of tax rate can increase the number of top

Table 5: Average Elasticity of International Mobility to Taxation

| | General | Top 10% | Top 10 to 50 % | Bottom |
|------------|---------|---------|-------------------|--------|
| General | 0.000 | 0.135 | -0.009 | -0.012 |
| Natives | 0.002 | 0.044 | 0.000 | -0.002 |
| Foreigners | -0.018 | 0.799 | -0.176 | -0.108 |

Notes: the elasticities are computed using the simulated assignments for the year 2016. Each elasticity is the weighted average of countries elasticities weighted by the ratio between the number of players in each group in the country and the number of players in each group in the sample.

players by 0.135%. This effect is stronger for foreigner (0.799) than for natives (0.044). The elasticities of players below the top 10% of the quality distribution are always small and negative. These results differs from the one found in the previous literature. For example, Kleven et al. (2013) found an elasticity around 1 for foreigners and around 0.15 for natives. This difference could be related to the fact that in our estimation we directly take into account the matching structure and the observed dimension of the market. However, in line with Kleven et al. (2013), our result suggest the presence of sorting effect on the base of marginal tax rates. Indeed, according to our results, an increase in the net of tax rate in one country can lead to an increase in the number of top players that displace players of lower quality. Given that the elasticity of medium and low quality players are very similar we can infer that the displacement effect is the same for both groups.

5 Conclusions

In this paper we have investigated the effect of marginal tax rates on the location decision process of high skilled tax payers using a dataset on European football

players between 2006 and 2016, and exploiting regional and national variation of tax rates.

We have analyzed this phenomenon estimating a two-sided matching model using a maximum score approach. This strategy has permitted to account for the matching structure of this labor market and to get rid of factors that affect the matching process but are usually hard available (such as wages and transfers between agents).

Whit regards to the sorting patterns based on quality, our result indicate that the matches are more valuable when they are between top players and team with high quality. Even though this effect is not surprisingly our results suggest that these effects are heterogeneous. Indeed, the coefficients associated with top quality players six times bigger than the one associated with medium quality players. The use of this variables has permitted to identify the effect of taxation on the utility of the match accounting for the one deriving from the quality of the match.

With regards to the effect of taxation, our results suggest that the marginal taxation affect directly only the location process of high quality workers and indirectly, through a displacement effect, the migration decisions of medium and low skilled worker. Indeed, the estimated coefficient related to the net of tax rate is significant and positive only for top players. This result is confirmed by the estimation of elasticities via a simulation algorithm. Indeed, our estimate of migration elasticities are positive only for top players and negative or null for the rest of the population. Therefore, according to our results, an increase in net of tax rate in one country is related with an increase in the number of top players that will displace the players with lower quality. Therefore, the taxation seems an effective tool to attract high-skilled workers.

Even though this displacement effect is in line with the previous literature, our point estimate of the elasticities are lower than usual. Indeed, the overall elasticities for foreigners and natives are around 0 and we find positive and larger estimates only considering players in the top 10% of the quality distribution. This could indicate that to control for the matching structure of the market matters in the estimation of the sensitivity of tax payers' location choices to marginal tax rates.

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A Appendix

A.1 The Net-Of-Tax Rate

In order to have a comprehensive net-of-tax rate we have collected data on different tax rates:

- τ_i top marginal income tax rate
- τ_e social security contributions on employer
- τ_w social security contributions on employee
- τ_{VAT} value added tax

Following Kleven et al. (2013) we define the net-of-tax rate as the increase in the worker's consumption when the firm's labor cost increases by 1 Euro. This rate is given by:

$$1 - \tau = \frac{(1 - \tau_i)(1 - \tau_w)}{(1 + \tau_{VAT})(1 + \tau_e)} \quad (\text{A.1})$$

We derive this formula we compute the marginal payroll taxes T_p given by the marginal increase in the firm's labor cost coming from the social contributions (Mertens and Montiel Olea, 2018):

$$T_p = \frac{\tau_e + \tau_w}{1 + \tau_e} \quad (\text{A.2})$$

It is important to note that $(1 + \tau_e)$ is the labor cost.

The marginal income tax T_i is computed on net earnings after that the payroll taxes are deducted:

$$T_i = \left(1 - \frac{\tau_e + \tau_w}{1 + \tau_e}\right) \times \tau_i \quad (\text{A.3})$$

Now we can compute the VAT using the same logic used for the payroll taxes. Indeed, we use the marginal increase in the VAT measured by:

$$\frac{\tau_{VAT}}{1 + \tau_{VAT}} \quad (\text{A.4})$$

Therefore, the marginal VAT tax T_{VAT} is computed as:

$$T_{VAT} = \left[1 - \frac{\tau_e + \tau_w}{1 + \tau_e} - \left(1 - \frac{\tau_e + \tau_w}{1 + \tau_e} \right) \times \tau_i \right] \times \frac{\tau_{VAT}}{1 + \tau_{VAT}} \quad (\text{A.5})$$

Now we can derive the marginal tax wedge step by step:

1. Marginal payroll taxes:

$$\frac{\tau_e + \tau_w}{1 + \tau_e}$$

2. Marginal payroll taxes plus marginal income tax:

$$\frac{\tau_e + \tau_w}{1 + \tau_e} + \left(1 - \frac{\tau_e + \tau_w}{1 + \tau_e} \right) \times \tau_i = \frac{\tau_e + \tau_w + (1 - \tau_w)\tau_i}{1 + \tau_e}$$

3. Marginal payroll taxes plus marginal income tax plus marginal VAT tax:

$$\frac{\tau_e + \tau_w + (1 + \tau_w)\tau_i}{1 + \tau_e} + \left[1 - \frac{\tau_e + \tau_w + (1 - \tau_w)\tau_i}{1 + \tau_e} \right] \frac{\tau_{VAT}}{1 + \tau_{VAT}}$$

Rearranging the previous equation we can derive the tax wedge τ^* :

$$\tau^* = \frac{\tau_e + \tau_w + (1 - \tau_w)\tau_i + \tau_e + \tau_{VAT}}{(1 + \tau_e)(1 + \tau_v)}$$

Now we can compute the net of tax rate:

$$1 - \tau^* = 1 - \frac{\tau_e + \tau_w + (1 - \tau_w)\tau_i + \tau_e + \tau_{VAT}}{(1 + \tau_e)(1 + \tau_v)}$$

$$1 - \tau = \frac{(1 - \tau_i)(1 - \tau_w)}{(1 + \tau_{VAT})(1 + \tau_e)}$$

A.2 The Matching Inequalities

In this section we show how it is possible to cancel wages from the utility functions exploiting the pairwise equilibrium concept. Suppose that we observe two matches: team a with player i and team b with player j . To save notation, let w be the transfer from a team to a player, τ be the income tax rate paid by the player, $V(a, i)$ be the utility of team a from hiring player i and $U(a, i)$ the utility of player

i from playing in team a . In this context we can write the payoff function of the team (π^T) and the player (π^P) as:

$$\pi^T(a, i) = V(a, i) - w_{ai} \quad (\text{A.6})$$

$$\pi^P(a, i) = U(a, i) + (1 - \tau_{ai})w_{ai} \quad (\text{A.7})$$

From the pairwise equilibrium we know that:

$$\pi^T(a, i) + \pi^P(a, i) + \pi^T(b, j) + \pi^P(b, j) \geq \pi^T(b, i) + \pi^P(b, i) + \pi^T(b, i) + \pi^P(b, i) \quad (\text{A.8})$$

Assume now that the team a can offer the transfer \tilde{w}_{aj} to make the player j indifferent between the two teams, so that:

$$U(a, j) + (1 - \tau_{aj})\tilde{w}_{aj} = U(b, j) + (1 - \tau_{bj})w_{bj} \quad (\text{A.9})$$

Taking logs and rearranging the equation we get²⁵:

$$\ln \tilde{w}_{aj} = \ln(1 - \tau_{bj}) + \ln w_{bj} + \ln U(b, j) - \ln U(a, j) - \ln(1 - \tau_{aj}) \quad (\text{A.10})$$

However, from the pairwise equilibrium we are assuming that:

$$\ln V(a, i) - \ln w_{ai} \geq \ln V(a, j) - \ln \tilde{w}_{aj} \quad (\text{A.11})$$

Therefore, substituting $\ln \tilde{w}_{aj}$ from the (A.10) in the inequality (A.11) we get:

$$\ln V(a, i) - \ln w_{ai} \geq \ln V(a, j) - [\ln(1 - \tau_{bj}) + \ln w_{bj} + \ln U(b, j) - \ln U(a, j) - \ln(1 - \tau_{aj})] \quad (\text{A.12})$$

²⁵This simplification depends on the fact that we use the MTR that does not depend on wages.

Using the same logic with player i and team b we can derive also the following inequality:

$$\ln V(b, j) - \ln w_{bj} \geq \ln V(b, i) - [\ln(1 - \tau_{ai}) + \ln w_{ai} + \ln U(a, i) - \ln U(b, i) - \ln(1 - \tau_{bi})] \quad (\text{A.13})$$

Combining the inequalities (A.12) and (A.13) we can cancel out the wages keeping the tax rates and the utilities of the two observed matches:

$$\begin{aligned} \ln V(a, i) + \ln V(b, j) + \ln U(a, i) - \ln(1 - \tau_{ai}) + \ln U(b, j) - \ln(1 - \tau_{bj}) \geq \\ \ln V(a, j) + \ln V(b, i) + \ln U(a, j) - \ln(1 - \tau_{aj}) + \ln U(b, i) - \ln(1 - \tau_{bi}) \end{aligned} \quad (\text{A.14})$$

Defining:

$$f(a, i) = \ln V(a, i) + \ln U(a, i) + \ln(1 - \tau_{ai}) \quad (\text{A.15})$$

$$f(b, j) = \ln V(b, j) + \ln U(b, j) + \ln(1 - \tau_{bj}) \quad (\text{A.16})$$

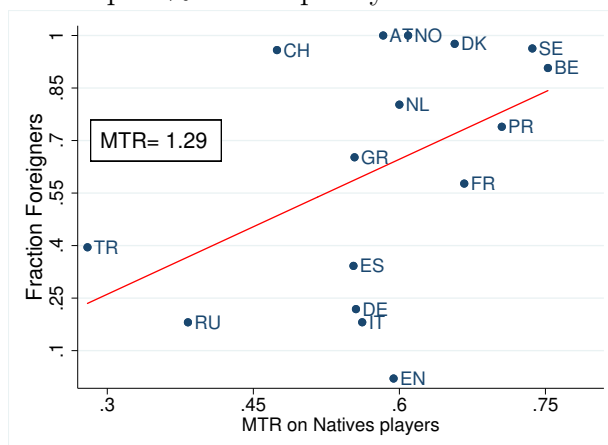
We can rewrite the previous inequality as:

$$f(a, i) + f(b, j) \geq f(a, j) + f(b, i) \quad (\text{A.17})$$

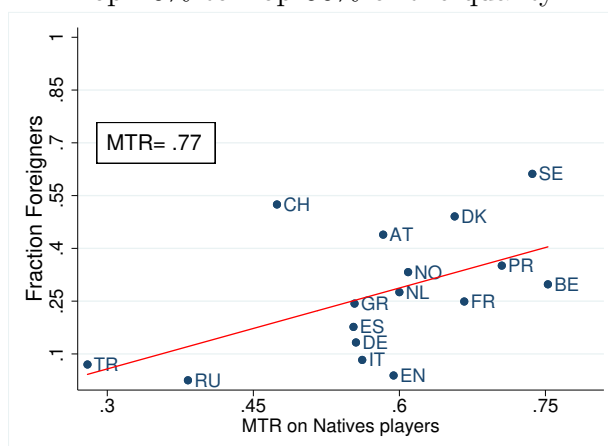
The inequality (A.17) says that the sum of matching production function of the two observed matches is greater than the one that the agents could obtain deviating from the equilibrium. Moreover, given that the wages have been canceled from the inequalities we do not need any information on them to compute the maximum score matching inequalities. This logic can be applied to all the agent-specific regressors.

In-migration of foreign players by quality

Top 10% of the quality distribution



Top 10% to Top 50% of the quality



Below the 50% of the quality distribution

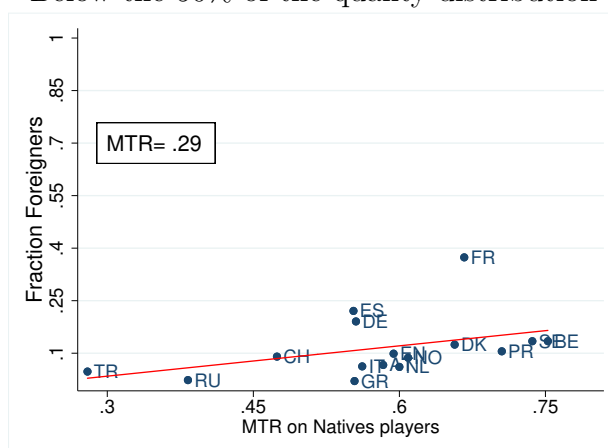


Figure A.1: Cross-Country Correlation between Tax Rates and Shares of Foreigners by Quality, 2006-2016

Notes: Each dot stands for one country: AT=Austria, BE=Belgium, DK=Denmark, EN=England, FR=France, DE=Germany, GR=Greece, IT=Italy, NL=Netherlands, NO=Norway, PR=Portugal, RU=Russia, ES=Spain, SE=Sweden, CH=Switzerland, TR=Turkey. The three plots show the relationships between the fraction of native players in each quality subgroup and the MTR valid in the origin country. In each plot we show the coefficient of the relevant MTR coming from a linear regression of the shares against MTR and a constant. All the plots refers to the entire period 2006-2016.

Table A.1: Origin-Destination flows

| Origin | Destination | | | | | | | | | | | | | | | |
|-------------|-------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| | AT | BE | DK | EN | FR | DE | GR | IT | NL | NO | PR | RU | ES | SE | CH | TR |
| Austria | 1959 | 1 | 18 | 25 | 1 | 141 | 23 | 21 | 19 | 7 | 14 | 5 | 3 | 1 | 28 | 38 |
| Belgium | 1 | 2125 | 5 | 109 | 44 | 54 | 20 | 43 | 307 | 7 | 8 | 20 | 21 | 0 | 6 | 19 |
| Denmark | 9 | 45 | 2008 | 65 | 38 | 90 | 4 | 36 | 128 | 103 | 1 | 2 | 21 | 67 | 6 | 10 |
| England | 1 | 6 | 9 | 2004 | 5 | 4 | 13 | 8 | 10 | 2 | 4 | 1 | 2 | 26 | 0 | 7 |
| France | 8 | 352 | 9 | 330 | 2758 | 83 | 86 | 156 | 32 | 13 | 72 | 23 | 157 | 6 | 77 | 28 |
| Germany | 105 | 20 | 23 | 79 | 8 | 2775 | 29 | 25 | 69 | 14 | 11 | 13 | 38 | 12 | 24 | 94 |
| Greece | 7 | 30 | 3 | 26 | 8 | 60 | 2774 | 58 | 18 | 0 | 13 | 1 | 17 | 2 | 4 | 8 |
| Italy | 2 | 8 | 0 | 68 | 32 | 45 | 33 | 3926 | 9 | 0 | 13 | 19 | 70 | 0 | 58 | 6 |
| Netherlands | 16 | 82 | 37 | 165 | 21 | 107 | 20 | 52 | 2927 | 4 | 25 | 21 | 49 | 17 | 11 | 44 |
| Norway | 8 | 12 | 64 | 50 | 16 | 35 | 5 | 7 | 33 | 1674 | 3 | 4 | 2 | 69 | 1 | 8 |
| Portugal | 0 | 23 | 5 | 89 | 61 | 38 | 96 | 61 | 8 | 1 | 2096 | 30 | 207 | 2 | 49 | 77 |
| Russia | 4 | 2 | 2 | 8 | 0 | 19 | 4 | 4 | 8 | 2 | 14 | 2254 | 7 | 2 | 3 | 1 |
| Spain | 52 | 44 | 2 | 254 | 11 | 50 | 204 | 91 | 27 | 0 | 60 | 28 | 3157 | 1 | 12 | 25 |
| Sweden | 13 | 24 | 163 | 63 | 32 | 45 | 30 | 48 | 126 | 178 | 9 | 19 | 12 | 2285 | 32 | 59 |
| Switzerland | 24 | 15 | 0 | 58 | 37 | 165 | 9 | 95 | 7 | 0 | 5 | 2 | 12 | 3 | 1282 | 11 |
| Turkey | 3 | 18 | 2 | 16 | 21 | 108 | 16 | 3 | 28 | 0 | 6 | 14 | 20 | 1 | 6 | 3795 |

Notes: The table shows the number of times when players citizen of one origin country have played in the destination countries considering all the sample period between 2006 and 2016.

Table A.2: Conditional Logit Estimation

| | CLOGIT | CLOGIT | CLOGIT | CLOGIT | CLOGIT |
|---|------------------|-------------------|-------------------|-------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Native | 4.310 (0.013) | 4.310 (0.013) | 4.322 (0.013) | 4.322 (0.013) | 4.336 (0.013) |
| $(1 - \tau) \times Top_{10}$ | 1.898 (0.083) | 1.898 (0.083) | 1.569 (0.101) | 1.569 (0.101) | 1.576 (0.101) |
| $(1 - \tau) \times Top_{1050}$ | 0.974 (0.044) | 0.972 (0.044) | 0.714 (0.045) | 0.714 (0.045) | 0.707 (0.045) |
| $Quality_{team} \times Quality_{player}$ | 0.030 (0.003) | 0.034 (0.004) | | | |
| $Quality_{team} \times Top_{10}$ | | | 1.450 (0.018) | 1.450 (0.018) | 1.544 (0.023) |
| $Quality_{team} \times Top_{1050}$ | | | 0.281 (0.006) | 0.281 (0.006) | 0.289 (0.006) |
| $Quality_{team} \times Young$ | | -0.006 (0.005) | -0.068 (0.004) | -0.068 (0.004) | |
| $Quality_{team} \times Top_{10} \times Young$ | | | | | -0.010 (0.001) |
| $Quality_{team} \times Top_{1050} \times Young$ | | | | | -0.013 (0.001) |
| Observations | 1.231e+07 | 1.231e+07 | 1.231e+07 | 1.231e+07 | 1.231e+07 |
| Pseudo R2 | 0.326 | 0.326 | 0.346 | 0.346 | 0.346 |

Notes: This table presents the CLogit estimates of the specifications of table 2.