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Abstract

The analysis of football transfers is hampered by selectivity bias. In most empirical estimations, simple regression is used and selectivity is ignored. In this paper we propose an estimation method that corrects for sample selectivity and allows the use of more observations in a simple manner. The ordered probit estimates point in a similar direction as the estimates from commonly applied estimation techniques but the significance is higher.

Keywords: Football transfers, sample selectivity, ordered probit model.

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1 Introduction

The remuneration of football players is an intriguing issue. Economists believe that it is closely related to the productivity of the players. Players are hired by teams in the hope that they strengthen the team so that the sporting success is increased. The salary of the player then depends on the value he adds to this. Sporting success is reflected in financial success through increased income by larger match attendance, higher earnings from merchandising and advertisements, better sponsorship deals, etc. However, hiring a player is an investment with a risky outcome. The player's productivity is likely to fluctuate in time and depends on the quality of the rest of the team and the quality of the opponents of the team. Furthermore, the relation between sporting success and financial returns is insecure and depends on factors like the economic situation, whether the national team is doing well, the popularity of other sports etc. The costs of hiring a player are threefold: (i) the player has to be paid a salary, (ii) if the player still has a contract with another football club a transfer fee needs to be paid to compensate the former club for their lost productivity during the remaining term of the contract and (iii) the investments the former club did to bring the player at his present level of football productivity has to be compensated. The latter part is quite likely to be relatively small and negatively related to the productivity of the player. A good football player will start to be productive at a younger age. Due to the lack of salary data in European football, many researchers have relied on published transfer fees to measure productivity in football (e.g. Carmichael and Thomas (1993); Speight and Thomas (1997); Carmichael and Simmons (1999); Dobson et al. (2000); Gerrard and Dobson (2000); Medcalfe (2008). Apparently, it is widely believed that there is a strong positive correlation between football salaries, transfer fees and productivity.

Frick (2007) gives an overview of the investigations on transfer fees in football. One of the problems with the analysis of transfer fees is sample selectivity. Although this phenomenon is often ignored, Frick (2007) points at at least two different sources of sample selectivity, i.e. (i) not all players have the same probability to experience a transfer and (2) the subsample of transferred players for which the transfer fee is actually published might not be a random sample from all transfers. We believe that especially the second source is very serious because the relative number of transfer fees actually becoming public is very modest. According to Sky Sports (2012) and Sky Sports (2013) there were about 300 players transferred to another team in England in the football season 2011-2012 and more than 700 players in 2012-2013. The transfer fees are only known for about 38% in 2011-2012 (115 players) and less than 9% (62 players) in 2012-2013. Part of the explanation of missing transfer fees is that, since the Bosman-arrest, transfer fees can only be demanded by the club the player wants to leave if he still has a contract. Another part of the explanation is that a substantive part of the players are unable to find a new professional soccer club after their contract expired. In our sample 165 out of 373 players (44.2%) were unable to get a new contract. As a result the possibility of sample selectivity is far from inconceivable. Carmichael and Simmons (1999) deal with the first type of sample selectivity mentioned by Frick (2007), the second type appears to be largely ignored.

To investigate transfers we will exploit the available information differently. Our method has two advantages. First, we solve the problem of sample selectivity due to observing a nonrandom sample of transfers with known transfer fees and second, we estimate on a much larger sample. It is always observed which football teams are involved in the transfer. If it would be possible to rank the teams according to their football quality, it can be assessed whether the transfer is an improvement or a deterioration. We believe that large improvements are accompanied by a high new salary, a high transfer fee when applicable and a high productivity. To do this, we need a method to completely rank the European professional football teams. Two problems have to be overcome: (i) how to rank football teams within a national league and (ii) how to rank football teams across the European national leagues. Within a country competition a ranking is relatively straightforward. The average rank at the closure of the competition across a number of years can be calculated and from this we can rank the football teams in a national competition. Alternatively, we can look at the average number of points earned by the team relative to the other teams in the league across a period of time and rank the teams accordingly. After some experimentation we chose for the second method. To compare teams across different countries we make use of the UEFA country coefficient. It is based on the achievements of clubs participating in either the UEFA Champions League or the UEFA Europe League. Points are awarded for wins, draws and reaching the last sixteen, quarterfinals, semi-finals or final of one of the competitions. The country coefficient is calculated by taking the average number of points earned in the last five years.[1] [2] We combine the national competition results and the UEFA country coefficient in the following way to obtain a European club coefficient:

$$\text{ClubCoeff}_i = \left(\sum_{s=2008-2009}^{2011-2012} \frac{Results_{ijs}}{\sum_i Results_{ijs}} \right) * \text{UEFACountryCoeff}_j \quad (1)$$

where j indicates the country, s the football season (ranging from seasons 2008-2009 up to 2011-2012) and i is the football club under consideration. $Results_{ijs}$ is the number of points earned by club i in the national first league of country in seasons.[3] The resulting club coefficients are ranked and the top 75 clubs are listed in table 1. The ranking appears to be quite sensible. Spain, England, Germany and Portugal appear to have the strongest competitions. Somewhat surprising is that Italian clubs are relatively low on our list. However this also holds for the UEFA club ranking. The correlation between the ranks based on our and the UEFA method is quite high: 0.842. Still, we do not believe that our ranking is perfect. It probably is a good reflection of the sportive success of a football club but that does not necessarily mean that clubs high on the list are willing to pay high salaries or high transfer fees. This is illustrated by the total absence of Turkish clubs in our Top 75. Fenerbahçe SK is only ranked as 122 on our list and Galatassaray AŞ only as 152,[4] whereas it is well known that Turkish

[1] The precise way countries are ranked is given on http://www.uefa.com/memberassociations/uefarankings/country/

[2] The UEFA also published an European club ranking (http://www.uefa.com/memberassociations/uefarankings/club/). We can not utilize this ranking because many clubs are not present on the list because they did not participate in one of the international UEFA competitions in the last five years.

[3] The information on the number of points earned in a season is taken from www.vi.nl, the website of Voetbal International, the leading football magazine of the Netherlands. It contains information on all European first football leagues.

[4] In the UEFA club ranking Fenerbahçe SK is listed as the number 51 and Galatassaray AŞ as the number 44. The UEFA club ranking contains fewer clubs than our ranking.

clubs pay relatively high salaries. Because of this imperfection we propose not to use the complete ranking on the basis of our method but instead look at whether the transfer can be considered to be an improvement, neither an improvement nor a decline, or a decline.[5]

Define

$$y_i^* = Rank_{ti} - Rank_{fi} \tag{2}$$

as the difference in the rank of the club the player is transferred to and the rank of the club he is transferred from. We specify:

$$y_i^* = \beta' x_i + \varepsilon_i \tag{3}$$

where x_i is a vector of characteristics of the football player involved in a transfer.[6] This difference in rank is actually observed and therefore we could simply use regression to estimate β. However, we believe that the ranking is a tentative and not an exact result and therefore we also propose to use an alternative way of modeling transfers. On the basis of y_i^* we distinguish improvements and declines in two different ways. First, we consider a classification on absolute differences in rank:[7]

$$y_{1i} = \begin{cases} 1 & \text{if} \quad y_i^* < \alpha_1 \\ 2 & \text{if} \quad \alpha_1 < y_i^* < \alpha_2 \\ 3 & \text{if} \quad y_i^* > \alpha_2 \end{cases} \tag{4}$$

where we choose specific numbers for α_1 and α_2.[8] Second, we consider a classification on relative differences in rank:

$$y_{2i} = \begin{cases} 1 & \text{if} \quad y_i^* < -0.2 * Rank_{fi} \\ 2 & \text{if} \quad -0.2 * Rank_f < y_i^* < 0.2 * Rank_{fi} \\ 3 & \text{if} \quad y_i^* > 0.2 * Rank_{fi} \end{cases} \tag{5}$$

Under the assumption of a standard normal distributed error term, the resulting models are ordered probit models with known thresholds. The parameters are estimated with the method of maximum likelihood.

2 Data

We have data available on 373 transfers in the English Premier League in the season 2011-2012. In 55 cases we were able to retrieve the transfer fee by using information from Sky Sports (2012)

[5]We also tried using only five categories (big improvement, improvement, neutral, decline, big decline) but this reduces the already limited number in especially the category improvement even further. The estimation results were very similar.

[6]Of course we can immediately apply OLS on this equation. The estimation results show very marginal significance (p-value of the F-test on regression = 0.218), indicating that our precise ranking itself might not be very informative.

[7]We experimented with different class sizes both in (4) and (5). The estimation results remained remarkably constant as long as sufficient numbers of observations were left in each of the categories.

[8]In Table 4, $\alpha_1 = -25$ and $\alpha_2 = 25$. In Table 5, $\alpha_1 = -100$ and $\alpha_2 = 0$.

and http://www.transferleague.co.uk/. Player characteristics were taken from different sources. The English football club Manchester City provided very extensive information on match statistics of all the players in the Premier League 2011-2012.[9] These match statistics are collected by Opta Sports. Personal information of the players is collected from www.transfermarkt.de. The information on the website contains information about the origins, age, height, preferred foot and position of a player. Most explanatory variables used are self explanatory. Some other variables need clarification:

- %substitute = number of appearances as a substitute/number of matches played;
- %golden sub = number of appearances as a substitute and scoring a goal/number of substitutions;
- %penalty scored = number of scored penalties/number of scored goals;
- %start in match = number of times starting in a match/number of matches played;

Table 2 contains sample characteristics.

Different dependent variables are used. Information on transfer fees, used in the estimations presented in Table 3, is provided in Table 2. In Table 4, using the absolute difference in ranking, the number of transfers indicating an improvement is 22 (5.9%) and 345 (92.5%) of the transfers are declines.[10] For the relative difference in ranking these numbers read 23 (6.2%) and 338 (90.6%). The dependent variable in the first estimation presented in Table 5 represents 4 categories: (1) the player having no club, 165 observations (44.2%); (2) the player experiencing a large decline transfer, 137 observations (36.7%); (3) the player experiencing a small decline or no decline, 45 observations (12.1%); and (4) the player experiencing an improvement, 26 observations (7.0%).

3 Estimation results

The first part of Table 3 presents estimation results on the linear regression of the transfer fee (in millions of pounds) on the characteristics of the football player and some other variables for the subsample of observed and positive transfer fees. Only 55 observations remain. The estimation presented here is the final result of an extensive search for significant player characteristics involving many more characteristics then the ones used in the final estimation. Significance is very modest. We only find effects of age and the number of minutes played in the season before the transfer. Age has a positive effect on the transfer fee up to the age of 26. Actually playing games has a positive effect on the transfer fee. If the player was relatively successful in scoring as a substitute, the transfer fee appears to be higher. Note the relatively high R^2 of almost 75%. The results presented here reflect what is usually done in the analysis of football transfers.

[9] We have a wealth of individual information available but we were unable to get significant results with respect to more sophisticated variables.

[10] In Table 4 not finding a new club is put down as a large decline.

To investigate selection bias[11] in a straightforward but crude way, consider the second part of Table 3. It present the ML-estimates of the Heckman-selectivity model on the complete sample of 373 transfers (club changes - check above how defined: leaving a club but sometimes finding no other one). The probability of observing the transfer fee has some highly significant determinants. Again age seems to be important just as the number of matches played. This last variable is not significant in the transfer fee equation and therefore avoids that we only identify parameters because of nonlineairities in the model.[12] The correlation coefficient is estimated to be about 0.5, which is considerable, but it is not significant. Note that the significance of the transfer fee equation seems to be somewhat enhanced. Taller player seem to be less attractive on the player market, although its effect is only marginally significant. The effect of age, although the estimated coefficients changed considerably compared to the OLS regression, remains the same. The transfer fee increases up to the age of about 26, and decreases thereafter. Actually playing and not being a substitute usually increases the transfer fee. A somewhat surprising result is the positive effect of red cards received. The estimated coefficient seems to be quite large but as can be seen from Table 2 the incidence of receiving a red card is very small. Again being successful as a substitute has a positive impact on the transfer fee. As noted the selectivity correction here is rather crude. Players not finding a new club are treated the same as players for which no transfer fee is observed but who actually found a new club.

In Table 4 we present estimation results of the ordered probit model on transfers which, according to our ranking as explained in the introduction, are a decline, neithere a decline nor an improvement or an improvement. We do not consider this to be the optimal model because the number of observations in the two top categories is very modest. On top of that, being unable to find a new club is considered to be a decline and is not treated as a separate category. Still, the estimation results are surprisingly significant and this holds for both absolute and relative difference in rank. The differences in the estimation results with the absolute and relative measure are modest: there are no sign reversals and the significance is very similar. Again there is a positive effect of age on the quality of the transfer up to the age of 26 or 27 depending on the specification considered. Being left-footed is not a positive player characteristic. Attackers, midfielders and defenders are in higher demand than goalkeepers. Note the very similar estimates for the non-goalkeepers. Apparently, the position in the field, as long as it is not the goal, has no impact on the quality of the transfer. Scoring goals, as long as they are not penalties, increases the probability of moving to a better club. Again, actually playing has a positive effect. The average number of yellow and red cards now both have a significant and negative impact in the probability to move to a better club. Golden substitutions now have a significant negative effect. A final result is that transfer free players have a worse chance to go to a better club. This is not very surprising. Note that this explanatory variable might be endogenous. However, excluding this variable hardly changes the parameter estimates. If we compare the estimation results of Table 3 with those in

[11] Since we restrict our analysis to players that left a football team, the selectivity discussed by Carmichael and Simmons (1999) is ignored.

[12] The p-value of this variable when added to the transfer fee equation is 0.122.

Table 4, first column and if we concentrate on the significant effects in Table 3, first column, we can conclude that if we correct for the difference in scaling the estimation results are very similar. The estimated coefficient of 'Age' is 1.096 in Table 3 and if we adapt the scaling such that the estimate of 'Age' in Table 4 is also 1.096, the estimated coefficients of 'Age' and 'Average minutes played' change to -0.020 and 0.017 which are both almost equal to the equivalent estimates in Table 3.

In Table 5 we present ordered probit estimates that explicitly distinguish players that left a club and where unable to find a new club from players who found a new club. In the first part of the table we present estimates of an ordered probit model with four ordered categories (no new club, big decline, small decline and improvement (or neutral)). The advantage of choosing these categories is that the observations are more evenly spread. In the second part of the table we ignore the players that were unable to find a new club, but maintain the other categories. The overall significance seems to have diminished somewhat, but the conclusions are very similar. The age of 26 seems to be an optimal age to get a good transfer. Goalkeepers are in a disadvantaged position and actually playing and not sitting on the bench remains important. Being transfer free is a con to get a good transfer.

4 Conclusion

In this paper we proposed a simple method to overcome the problem of selectivity due to not observing all transfer fees and a considerable number of players being unable to find a new club. Being able to use more observations improves the significance. Only a few player characteristics have a positive effect on making a good transfer. Age, average number of minutes played and not being a goal keeper are the most important determinants. A surprising result is that the number of goals scored does not seem to have a big impact. Our proposed method appears to yield better estimation results than traditional methods on our sample. Still, the correction for selectivity we use is not very sophisticated: we ignore potential selectivity due to different likelihoods of changing clubs as analyzed by Carmichael and Simmons (1999). To take account of this, a more elaborate Heckman-like setup could be employed. To do this, probably more observations are needed than we have available.

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Table 1: Top 75 of European football teams according to our calculations.

Rank		Rank		Rank	
1	Barcelona	26	Villarreal	51	FC Twente
2	Real Madrid	27	Internazionale Milan	52	Osasuna
3	Manchester United	28	Everton	53	Borussia Mönchengladbach
4	FC Porto	29	Hamburger SV	54	Espanyol
5	Bayern München	30	FC Basel	55	PSV
6	Borussia Dortmund	31	Werder Bremen	56	BSC Young Boys
7	Benfica	32	Real Mallorca	57	Olympiakos Piraeus
8	Chelsea	33	Atheltic de Bilbao	58	Red Bull Salzburg
9	Shakhtar Donetsk	34	1899 Hoffenheim	59	Vit'Guimares
10	Dinamo Kiev	35	Hannover 96	60	Girondins Bordeaux
11	Arsenal	36	Juventus	61	Marítimo Funchal
12	Valencia	37	Aston Villa	62	Paris Saint-Germain
13	Manchester City	38	Lille	63	Napoli
14	Bayer Leverkusen	39	Ajax	64	Anderlecht
15	Sporting Braga	40	Dnjepr Dnjepropetrovsk	65	AZ Alkmaar
16	Schalke 04	41	Zenit Sint-Petersburg	66	Stoke City
17	Liverpool	42	Malaga	67	Udinese
18	Sevilla	43	Rubin Kazan	68	FC Kopenhagen
19	VfB Stuttgart	44	AS Roma	69	Spartak Moskou
20	Sporting Lissabon	45	Getafe	70	1. FC Köln
21	Tottenham Hotspur	46	National Madeira	71	FC Zürich
22	Atlético Madrid	47	Olympique Marseille	72	Sporting Gijon
23	AC Milan	48	Olympique Lyon	73	Lazio
24	VfL Wolfsburg	49	Fulham	74	Rapid Wien
25	Metalist Kharkiv	50	CSKA Moskou	75	Lokomotiv Moskou

Table 2: Descriptive statistics

Variable	Mean	Std Dev.	Minimum	Maximum
Transfer fee (in millions of pounds, if observed)	5.905	7.959	0.4	45
Transfer fee known	0.148	0.355	0	1
Age	23.316	4.888	17	39
Height (in centimeters)	182.354	6.393	168	201
Left-footed	0.206	0.405	0	1
Left-&Right-footed	0.105	0.306	0	1
Attacker	0.257	0.438	0	1
Midfielder	0.349	0.477	0	1
Defender	0.290	0.454	0	1
Average goals	0.018	0.066	0	0.583
Average minutes played	18.276	29.086	0	90
Average yellow cards	0.031	0.079	0	0.5
Average red cards	0.002	0.012	0	0.1
%substitute	0.162	0.304	0	1
%golden sub	0.005	0.027	0	0.2
%penalty scored	0.007	0.066	0	1
Number of matches played	4.858	9.369	0	38
Mid-season transfer/other vars (Heckman)				
Transfer free	0.611	0.487	0	1

Table 3: OLS and Heckman model estimates.

	OLS		Heckman	
Variable	Estimate	Std Error	Estimate	Std Error
Constant	6.610	(7.166)	-12.042	(9.807)
Age	1.096	(0.520)*	1.463	(0.732)*
Age^2	-0.021	(0.010)*	-0.028	(0.014)*
Height	-0.032	(0.024)	-0.034	(0.018)◊
Left-footed	0.016	(0.342)	-0.004	(0.255)
Left-&Right-footed	0.267	(0.329)	0.275	(0.241)
Attacker	-0.244	(0.660)	-0.205	(0.486)
Midfielder	0.186	(0.683)	0.208	(0.498)
Defender	-0.247	(0.596)	-0.264	(0.433)
Average goals	0.758	(1.591)	0.674	(1.181)
Average minutes played	0.017	(0.005)**	0.020	(0.008)**
Average yellow cards	-0.662	(1.776)	-0.836	(1.338)
Average red cards	15.184	(9.956)	14.573	(7.439)*
%substitute	-0.955	(0.595)	-0.905	(0.446)*
%golden sub	6.377	(3.620)◊	6.830	(2.782)*
%penalty scored	-1.257	(1.244)	-1.237	(0.940)
Mid-season transfer	-0.184	(0.298)	-0.240	(0.237)
Constant			-19.058	(3.625)**
Age			1.425	(0.291)**
Age^2			-0.028	(0.006)**
%start in match			-0.466	(0.441)
Number of matches played			0.058	(0.014)**
R^2		0.744	Correlation	0.504
SD regression		0.786		0.636
p-value F test on regression		0.001		0.000
Number of observations		55		373

**,*,◊ = significant at 1%, 5%, 10%. Dependent variable: ln(transfer fee).
Dummy variables displaying the region of birth of the player were also used in the estimation.
Number of matches played when added to the linear part of the specification is not significant.

Table 4: Ordered Probit estimates on decline/neutral/improvement

	Ordered Probit			
	Absolute difference		Relative difference	
Variable	Estimate	Std Error	Estimate	Std Error
Age	0.658	(0.231)**	0.474	(0.344)
Age^2	-0.012	(0.005)**	-0.009	(0.007)
Height	-0.012	(0.016)	-0.003	(0.024)
Left-footed	-0.587	(0.298)*	-0.734	(0.374)◇
Left-&Right-footed	-0.257	(0.347)	-0.094	(0.388)
Attacker	3.467	(0.164)**	4.508	(0.184)**
Midfielder	3.372	(0.191)**	4.871	(0.182)**
Defender	3.689	(0.163)**	4.544	(0.242)**
Average goals	3.229	(0.193)**	3.600	(0.314)**
Average minutes played	0.010	(0.004)**	0.015	(0.001)**
Average yellow cards	-1.786	(0.140)**	-1.294	(0.189)**
Average red cards	-1.973	(0.006)**	-2.896	(0.049)**
%substitute	-0.461	(0.430)	-0.108	(0.439)
%golden sub	-0.896	(0.032)**	-2.411	(0.026)**
%penalty scored	-1.378	(0.097)**	-1.760	(0.149)**
Mid-season transfer	0.212	(0.250)	0.185	(0.278)
Transfer free	-0.875	(0.292)**	-0.679	(0.346)*

**,*,◇ = significant at 1%, 5%, 10%.

Dummy variables displaying the region of birth of the player were also used in the estimation.

Table 5: Ordered Probit estimates on no club/big decline/small decline or neutral/improvement

	Ordered Probit			
	Including no new club found		Excluding no new club found	
Variable	Estimate	Std Error	Estimate	Std Error
Age	0.574	(0.184)**	0.533	(0.307)◊
Age^2	-0.011	(0.004)**	-0.010	(0.006)◊
Height	-0.011	(0.011)	0.004	(0.017)
Left-footed	-0.207	(0.158)	-0.153	(0.244)
Left&Rightfooted	-0.030	(0.218)	-0.081	(0.330)
Attacker	0.766	(0.285)**	0.639	(0.568)
Midfielder	0.768	(0.286)**	0.880	(0.575)
Defender	0.801	(0.267)**	0.621	(0.542)
Average goals	0.431	(1.120)	1.924	(1.424)
Average minutes played	0.011	(0.003)**	0.010	(0.004)**
Average yellow cards	0.037	(0.916)	-2.321	(1.583)
Average red cards	0.381	(5.233)	6.310	(6.962)
%substitute	-0.484	(0.230)*	0.007	(0.373)
%golden sub	-3.894	(2.393)	-0.979	(2.735)
%penalty scored	-1.357	(0.913)	0.690	(1.000)
Mid-season transfer	0.004	(0138)	0.095	(0.221)
Transfer free	-0.694	(0.167)**	-0.437	0.235◊

**,*,◊ = significant at 1%, 5%, 10%.

Dummy variables displaying the region of birth of the player were also used in the estimation.